HOUSING AND MARKET-BASED INTERMEDIARIES IN THE CYCLE: EVIDENCE FROM AN ESTIMATED DSGE MODEL

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HOUSING AND MARKET-BASED INTERMEDIARIES IN THE CYCLE: EVIDENCE FROM AN ESTIMATED DSGE MODEL

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I study housing and market-based financial intermediaries (MBIs) as *sources* of business cycles versus *propagation mechanisms* of traditional macroeconomic shocks using macro and financial data from 1985-2011. Combined, shocks originating in the MBI funding market and to housing demand account for 4% – 42% of fluctuations in macro, financial, and house price data. Shocks originating from MBIs account for the initial phase of the housing boom from 2001-2004 and dynamics in credit, leverage, and investment since the late 1990s. Housing demand shocks account for the 2006 collapse in housing prices but are otherwise unimportant. A decomposition of the Great Recession supports a growing consensus that it was an unprecedented confluence of large shocks, only some of which were directly related to the housing market and financial sector. A steady-state analysis of the effects of financial deregulation reveals that higher MBI leverage cushions the economy from traditional macro shocks but at the cost of making it more vulnerable to financial sector shocks.

BIOGRAPHICAL SKETCH

John Owsley was born in Columbia, Missouri on September 5, 1984. Growing up in Columbia, John began his undergraduate studies at the University of Missouri-Columbia in August, 2003 with the intention of majoring in accounting and becoming a Certified Public Accountant (CPA). After taking introductory microeconomics, John developed a passion for understanding how markets work and interact. In his sophomore year, John changed his major to economics and set a goal of earning a Ph.D.. After graduating with honors, *summa cum laude*, in May 2007 with a BS in economics and minor in mathematics, John stayed at the University of Missouri one additional year to earn an MA in economics. In August 2008, John began his doctoral studies at Cornell University in Ithaca, New York. John successfully defended his dissertation in the spring of 2013, and looks forward to facilitating business in the private sector by applying the skills in economic analysis learned throughout his studies. In the coming year, John plans to earn the CPA credential to better translate the potency of economic analysis into the language of business.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Together with its severity and duration, the Great Recession is unique among postwar recessions in its seeming precipitating sources: a nationwide collapse in house prices and financial crisis the likes of which had not been seen since the Great Depression. The steep rise in house prices and greater presence of highly leveraged market-based financial intermediaries (MBIs) prior to the recession makes these precipitating sources seem all the more convincing.[1] But nearly three years after the end of the recession, "assigning blame" to the housing market and financial sector has proven to be complicated. After reviewing 21 books on the Great Recession written by academics, economic journalists, and policymakers, Lo (2012) finds almost a 50-50 split. Half lay the blame to the housing market, with the seeds of the crisis sown beginning with the bursting of the house price bubble in 2006. The other half attributes the liquidity crisis faced by MBIs in late 2007 and 2008 as the shock which did the most damage. Hamilton (2009) looks beyond housing and MBIs, presenting evidence that the oil price price spike of 2007-2008 was the initial shock that caused a decline in consumption and led to the bursting of the housing bubble and subsequent financial collapse.

The above competing theories of the causes of the Great Recession are attempts to answer a broader question: to what extent are housing and MBIs *sources* of business cycles versus *propagation mechanisms* of other shocks? In this paper I assess the importance of both roles in the U.S. using data from 1985-2011.

First, I disentangle the business cycle importance of (a) shocks originating in an MBI-dominated financial sector with endogenous leverage, versus (b) shocks originating in a housing market with collateralized household mortgage debt. The shocks need to be

[1] Examples of MBIs include security broker-dealers, finance companies, and asset-backed security issuers. I review the key features of MBIs relevant for this analysis in Section 2.

disentangled because households typically need to access the credit market to purchase a home, making housing and credit complementary goods. Given this relationship, it is not obvious what is the source of the cycle - is it an increase in the demand for housing, increase in the supply of credit, or a shock originating elsewhere?[2]

Second, in light of financial deregulation which affected both MBIs and mortgage lending over the past 30 years, I assess how long run structural changes which allow for higher household and MBI leverage affect the extent to which these sectors propagate other economic shocks.

The framework of the analysis is a standard New Keynesian model with disturbances to preferences, technology, monetary policy, and production-sector credit disturbances, as in Smets and Wouters (2007) and Jermann and Quadrini (2011). The model is augmented with housing, heterogenous households, entrepreneurs that operate the production sector, and collateral constraints on debt, as in Iacoviello (2005).[3] The housing market becomes a source of fluctuations through shocks to housing preferences (housing demand shocks). I further augment the model with a financial sector of MBIs that lends to households and entrepreneurs. To capture the main characteristic of MBIs - market-based funding constraints - the supply of credit is determined through endogenous leverage constraints on MBIs, as in Gertler and Karadi (2011). MBIs become a source of fluctuations through a shock originating in the funding market for MBIs (financial funding shocks). The model is estimated using Bayesian methods. In addition to using standard macroeconomic data, I identify the financial funding, entrepreneur credit, and housing demand shocks using data on house prices, mortgage and business credit, and leverage of U.S. security broker-dealers.

[2]Boom-bust cycles in housing are typically associated with boom-bust cycles in credit and financial innovation. This is a feature robust across both advanced and emerging economics. For reduced form evidence, see Claessens et al. (2010); Ahearne et al. (2005); Tsatsaronis and Zhu (2004); Cardarelli et al. (2009); Goodhart and Hofmann (2008); Reinhart and Rogoff (2009).

[3]Iacoviello and Neri (2009) show that an estimated version of this model captures the business cycle dynamics of macro variables and house prices over the period 1965-2006.

The importance of financial funding and housing demand shocks as sources of business cycles is nontrivial: combined, they account for at least 15% of fluctuations in investment, the t-bill rate, house prices, credit, and broker-dealer leverage. Traditional macro shocks together still account for the majority of fluctuations in all macro and financial variables, explaining anywhere from 56% (house prices) to 93% (consumption) of business cycle movements.

In relative terms, financial funding shocks are more important sources of business cycle fluctuations than housing demand shocks and have a pervasive influence over investment, house prices, credit, and leverage. Housing demand shocks, on the other hand, mainly drive own-market fluctuations in house prices and mortgage loans with little propagation to the rest of the economy.

I decompose the Great Recession and find that it was an unprecedented coincidence of large shocks, only some of which are financial and housing related. In my decomposition, negative technology shocks beginning in 2006 were the first disturbance. Technology shocks account for most of the decline in consumption and eventually contributed to declines in investment and credit. Housing demand shocks followed shortly thereafter, causing a collapse in house prices and contributing to declines in investment and further contractions in mortgage credit. Financial funding shocks were stimulative until 2007, mitigating the effects of negative technology and housing demand shocks on investment, credit, and leverage. But ultimately, large negative financial funding shocks dealt the final blow, causing significant further declines in investment and credit.

My explanation of the causes of the Great Recession closely resembles that of Stock and Watson (2012), who decompose the Great Recession using a structural dynamic factor model (DFM) and a large set of macroeconomic and financial data. The TFP shocks in my model show up as oil price shocks in the DFM used by Stock and Watson, corroborating Hamilton (2009) that the oil price spike of 2007-2008 was the initial negative shock that led to the downturn.

Since the recession has ended, my decomposition reveals that financial funding shocks account almost entirely for interest rates being at the zero-lower bound. In the recovery, negative cost-push shocks, positive discount factor shocks, and the zero-lower bound constraint on monetary policy have kept a lid on stronger gains in investment and consumption. In the Stock and Watson DFM, discount factor shocks show up as shocks to policy uncertainty.

Independent of their role as a source of fluctuations, housing and MBIs are equally important as influencing the volatility of business cycles. When steady state capital requirements are lowered, MBIs *cushion* the economy from macro and housing demand shocks by lowering volatility across macro variables, house prices, and credit. But, lower steady state capital requirements makes the economy more vulnerable to financial funding shocks - the volatility of macro and financial variables is higher in response to financial funding shocks and financial funding shocks become more important in driving business cycle fluctuations. Higher long-run loan-to-value (LTV) limits for households results in an unambiguous increase in macroeconomic and financial instability.

The steady-state analysis reconciles the pre-crisis belief that financial innovation could have been a contributor to the Great Moderation with the post-crisis skepticism of the benefits of financial deregulation and resurgence of the "Minksy moment." In terms of the Great Recession, the analysis confirms that not only was it a recession associated with uncharacteristically large financial and housing market shocks, but the economy was more responsive to them due to underlying trends in leverage brought about by financial deregulation.

To my knowledge, I am the first to address the relative business cycle importance of credit supply shocks vs. housing demand shocks in a structural model. Iacoviello and Neri (2009), Liu et al. (2010), and Walentin (2011) all assess the role of housing demand shocks in business cycle fluctuations, but none of these analyses explicitly include a financial sector or provides a decomposition of the Great Recession. Jermann and Quadrini (2011) accounts for the Great Recession with technology shocks and financial shocks strictly on firms, but ignores the role of housing and the financial sector itself as a source of fluctuations.

CHAPTER 2

MARKET-BASED INTERMEDIARIES: SOME FACTS AND FEATURES

In addition to being the focal point in the financial crisis, market-based intermediaries have played an important role in mortgage finance since the late 1980s. In this chapter I review key facts about MBIs and their role in the housing market as well as existing evidence of their role in the business cycle.

2.1 MBIs: Key players in the financial sector

The difference between traditional bank-based intermediation and market-based intermediation is displayed schematically in Figure C.1. Traditional bank-based intermediaries take (insured) deposits from households and lend the funds to other households. BBIs hold loans on their balance sheets. In contrast, market-based intermediation involves multiple, specialized financial institutions, each of which is funded through usually short-term, uninsured markets, and consists of buying mortgages from their originating institution, packaging them into marketable securities, and selling them to institutional investors or other MBIs as investments or collateral for more short-term funding.

Adrian and Shin (2010c) and Gorton (2010) document the increasing role of MBIs in the financial sector from the late 1980s. Total assets of bank and market-based intermediaries are plotted in Figure C.2. By the mid 2000s, assets of security broker-dealers nearly equaled that of commercial banks, with assets of security broker-dealers growing at an annual rate nearly eight-times that of commercial banks, nonfinancial corporations, and households. Adrian and Shin (2010a) break down the liabilities of security broker-dealers and find the majority of their funding comes from repo markets. To get a perspective of the importance of this short-term funding market for broker-dealers, Figure C.3 displays the value of outstanding repo contracts held by primary dealers, a subset of broker-dealers that bid at U.S. Treasury auctions, against the M1 money stock and financial commercial paper outstanding. The value of repos outstanding surpassed the M1 money stock from the mid 1990s and grew as large as four-times M1 by the eve of the crisis. As carefully documented by several authors, the epicenter of the financial crisis was the implosion of short- term funding markets for MBIs.[1] Commercial banks and other bank-based intermediaries suffered relatively little during the crisis, even increasing their assets in the aggregate well into the Great Recession (Adrian and Shin, 2010a).

2.2 MBIs: Key players in the mortgage market

Figure C.4 documents the increasing importance of MBIs in the growth of housing credit since the 1980s.[2] MBIs held over 60% of all mortgages outstanding at the peak of the housing boom. Using micro data on mortgage originations, several studies have suggested a causal link from MBIs to mortgage originations (i.e., a shift in the supply of mortgage funding instead of a shift in the demand for mortgages by households).[3] It is unclear as of yet the relative importance of specific factors within the financial sector - such as deregulation and advances in information technology, versus other macro factors such as historically low interest rates and the influx of global savings from abroad, in generating the increase in credit supply.[4]

The collapse of house prices beginning in 2006 is largely blamed for the loss of confidence in mortgage-backed securities that were used as collateral in repo contracts and

[1]See Brunnermeier (2009); Adrian and Shin (2009, 2010a); Gorton (2008) for detailed accounts of the crises and subsequent policy responses in the immediate aftermath.

[2]See Green and Wachter (2005) for a historical review of housing market finance, and Adrian and Shin (2010c) for a detailed analysis of the role of MBIs in mortgage finance from the 1980s to the crises.

[3]See Nadauld and Sherlund (2009), Gabriel and Rosenthal (2007), and Mian and Sufi (2008).

[4]See Rajan (2009) for an argument that the influx of savings from abroad played an important role in the credit and housing boom and Taylor (2007) for an argument that the Federal Reserve, through setting interest rates persistently below that suggested by the Taylor rule, contributed to the boom housing credit.

held on the balance sheets of MBIs (Brunnermeier, 2009; Gorton, 2008). However, a shock originating within the financial system could also be an important factor in the crises. I find evidence supporting this hypothesis in Owsley (2011). I study the effects of a housing demand shock on leverage of both bank and market-based intermediaries using a standard monetary VAR augmented with house prices, leverage, and credit. A negative house price shock causes MBI leverage to *increase* persistently for 8-10 quarters, the largest effect on broker-dealers. This response is inconsistent with the massive deleveraging of MBIs during the Great Recession and suggests the housing market alone cannot explain the crisis.

2.3 MBIs and the business cycle

There is also growing evidence that MBIs are important in understanding business cycle fluctuations beyond the recent financial crisis. Adrian et al. (2010) systematically investigate the forecasting power of all financial intermediaries in the U.S. Flow of Funds using balance sheet variables such as asset and leverage growth, and find that MBIs - in particular, broker-dealers - forecast real activity. In contrast, commercial banks posses no forecasting power.

Part of the reason MBIs seem to provide better information about financial market and overall macroeconomic conditions is the distinct behavior of their balance sheets. As documented by Adrian and Shin, broker-dealers engage in active management of their balance sheets. In contrast, commercial banks exhibit behavior akin to targeting a constant leverage ratio. The implicit market-based funding constraints faced by MBIs, which determine balance sheet positions, are more reflective of both macroeconomic and financial market conditions than the regulations which largely determine commercial bank balance sheets.

Gilchrist and Zakrajsek (2011b) provide further evidence that MBIs capture the importance of finance in the business cycle by decomposing corporate bond yields. Gilchrist and Zakrajsek decompose corporate bond spreads into two components: (1) that attributable to countercyclical movements in expected defaults and (2) an *excess bond premium* (EBP), which represents the capacity and willingness of the financial sector to bear risk beyond compensation for default. Gilchrist and Zakrajsek find the EBP to have superior GDP forecasting ability relative to the default-component of the corporate bond spread and find shocks to the premium to significantly affect consumption, investment, output and inflation.

Gilchrist and Zakrajsek show the EBP closely tracks credit-default swap (CDS) premiums of the U.S. primary dealers. A shock to the profitability of primary dealers leads to a persistent increase in their credit-default swap (CDS) premiums, which is mirrored by a nearly identical rise in the EBP. Since changes in CDS premiums reflect changes in the ability of MBIs to borrow funds that are lent out to the rest of the economy, then the close relationship between CDS spreads and the EBP suggest MBIs can be a important source of shocks which ultimately affects real activity.

2.4 Summary

Market-based intermediaries have dwarfed bank-based intermediaries in balance sheet growth, presence in the mortgage market, and role in the financial crisis. While there exists evidence that shocks to MBI balance sheets have real affects, there is little evidence to suggest how important outside shocks are relative to shocks originating with MBIs themselves. I now present the model which will be used to disentangle the importance of MBIs from traditional macro and housing shocks in the business cycle.

CHAPTER 3

THEORETICAL MODEL

3.1 The Model Economy

The model is a New Keynesian DSGE framework with three agents: impatient households, patient households, and entrepreneurs. Final goods consist of nondurable consumption and (durable) housing.

Patient households have a larger discount factor than impatient households and entrepreneurs. Patient households provide labor services to entrepreneurs, consume final goods, and lend to/operate the financial sector. Impatient households borrow from the financial sector, provide labor services to entrepreneurs, and consume final goods. Entrepreneurs also borrow from the financial sector, consume, and produce an intermediate good using household labor, capital, and housing. Impatient households and entrepreneurs are constrained in their ability to borrow by a standard collateral constraint.

Monopolistic retailers, owned by patient households and subject to nominal price rigidities, transform the intermediate good into the final consumption good.

Citing the importance of MBIs in the financial sector and mortgage market discussed in Chapter 2, I model a financial sector entirely composed of MBIs. The financial sector, operated by bankers who are members of patient households, channels retained earnings from previous lending and deposits from patient households into loans to impatient households and entrepreneurs. The borrowing constraint of bankers responds endogenously to changes in their expected future profitability, reflecting the market-based funding constraints faced by MBIs.

There are real rigidities in the form of adjustment costs and consumption habits. Business cycle dynamics originate from shocks to preferences (both inter and intratemporal), technology (both TFP and investment-specific), monetary policy, inflation (i.e., a "cost-push" shock), and credit tightness for entrepreneurs (similar to Liu et al. (2010) and Jermann and Quadrini (2011)). I call the collection of these disturbances "macro shocks." Rigidities and shocks of this form have demonstrated success in capturing business cycle dynamics of macroeconomic variables - see Christiano et al. (2005), Smets and Wouters (2007), and Jermann and Quadrini (2011). To give a role to the housing market and financial sector as a source of fluctuations, the model is augmented with a housing demand shock (Iacoviello, 2005) and a financial sector funding shock (developed below).

3.1.1 Households

Patient and impatient households are each in unit mass. A representative household within each group maximizes:

$$E_0 \sum_{t=0}^{\infty} (\beta_x G_c)^t z_t \left[\Gamma_x \ln(c_{x,t} - \epsilon_x c_{x,t-1}) + j_t j_x \ln(h_{x,t}) - \phi_x^h(h_{x,t}) - \tau_t \frac{n_{x,t}^{1+\chi_x}}{1+\chi_x} \right] \tag{3.1}$$

where $x = i, p$, $0 < \beta_i < \beta_p < 1$ and $c_{x,t}, h_{x,t}$, and $n_{x,t}$ are consumption, housing, and labor supply for household-type x at date t. Units of consumption are units of a Dixit-Stiglitz composite of a continuum of final goods with elasticity of substitution $\xi > 1$.

Households are subject to intertemporal preference shocks, captured by z_t, housing preference shocks, captured by j_t, and labor supply shocks, captured by τ_t. The shocks evolve according to

$$\ln(z_t) = \rho_z \ln(z_{t-1}) + u_{z,t}, \quad \ln(j_t) = \rho_j \ln(j_{t-1}) + u_{j,t}, \quad \ln(\tau_t) = \rho_\tau \ln(\tau_{t-1}) + u_{\tau,t}$$

where $u_{z,t}$, $u_{j,t}$, and $u_{\tau,t}$ are mean zero i.i.d. processes with variances σ_z^2, σ_j^2, and σ_τ^2, respectively.

The parameter ϵ_x measures habits in consumption, G_c is the growth rate of consumption along a balanced growth path, and Γ_x and j_x are scaling factors, discussed in more detail below. Households incur a utility flow from housing, given by $j_t j_x \ln(h_{x,t})$, but suffer a disutility cost of adjusting their housing stock of the form

$$\phi_x^h(h_{x,t}) = \phi_x \phi_x^h \left(\frac{h_{x,t}}{h_x} - 1\right)^2$$

The disutility cost of housing adjustment captures the search/psychological costs of buying a home which are distinct from costs associated with buying/selling other types of financial assets.

Discount factor heterogeneity between households induces heterogeneity in the marginal utility of saving across households. All else equal, impatient households have a higher marginal utility of immediate consumption relative to patient households, inducing a desire to trade intertemporally. In equilibrium, patient households save while impatient households borrow. Impatient households maximize (3.1) by choosing consumption $c_{i,t}$, labor supply $n_{i,t}$, housing $h_{i,t}$, and loans $b_{i,t}$ subject to their budget constraint

$$c_{i,t} + q_t h_{i,t} + \frac{1 + r_{b,t-1}}{1 + \pi_t} b_{i,t-1} = w_{i,t} n_{i,t} + q_t h_{i,t-1} + b_{i,t} \tag{3.2}$$

where q_t is the real price of housing (in terms of the composite final good), $r_{b,t}$ is the net nominal lending rate, $\pi_t = \frac{P_t}{P_{t-1}} - 1$ is the rate of inflation of the composite final good from date $t-1$ to date t, and $w_{i,t}$ is the impatient household real wage. Impatient households cannot commit to repay their debt to the financial sector and are free to default in period t on loans taken out at period $t-1$. In Appendix D I show that this type of limited enforcement problem between impatient households and the financial sector yields a borrowing limit for impatient households of the form

$$b_{i,t}(1 + r_{b,t}) \leq m_i E_t q_{t+1}(1 + \pi_{t+1})h_{i,t} \tag{3.3}$$

which is a standard collateral constraint as in Kiyotaki and Moore (1997) and Iacoviello (2005). The exogenous parameter $m_i \in (0, 1)$ is the steady state loan-to-value (LTV) ratio for residential mortgages.

When the borrowing constraint binds, housing is valued as collateral for borrowing in addition to it providing utility and being a store of wealth. Because of the collateral value of housing, housing preference shocks induce shifts in the demand for credit by impatient households. Housing preference shocks of this form have been used to measure the importance of the housing market in business cycle fluctuations by Iacoviello (2005), Iacoviello and Neri (2009), Liu et al. (2010), and Walentin (2011). Housing preference shocks are generally thought of being representative of any omitted characteristics of housing demand such as housing-related taxes and social housing preference shocks - see Iacoviello and Neri (2009) for a discussion. Liu et al. (2009) derives a micro founded model of housing preference shocks whereby changes in mortgage LTV ratios shift housing demand in a way consistent with housing preference shocks.

Each patient household is composed of a continuum of members of two types: workers and bankers. Workers supply labor, and bankers manage the household's own financial intermediary. At any moment in time the fraction $1-f$ of household members are workers and the remaining fraction f are bankers. Over time an individual can switch between the two occupations: a banker will remain a banker with probability θ, which is independent of history. Thus each period $(1 - \theta)f$ bankers exit and become workers - an identical mass of workers randomly become bankers, keeping the relative proportion of each type fixed.

The household provides its new bankers with initial capital, described below.

Two additional assumptions generate a meaningful role for the financial sector without increasing the level of heterogeneity in the model: (1) A household's savings is deposited in intermediaries other than those managed by their own household, and (2) within the family of any household there is perfect consumption insurance.

Patient households maximize (3.1) by choosing consumption, housing, labor supply, and deposits d_t subject to their budget constraint

$$c_{p,t} + d_t + q_t h_{p,t} = w_{p,t} n_{p,t} + \frac{1 + r_{t-1}}{1 + \pi_t} d_{t-1} + q_t h_{p,t-1} + \Pi_t \tag{3.4}$$

Patient households receive net nominal interest r_t from deposits as well as retained earnings from exiting bankers and profits from retailers, Π_t. Optimality conditions for all decision problems are in Appendix D.

3.1.2 Entrepreneurs (intermediate good sector)

Entrepreneurs combine capital, housing, and labor services of households to produce a homogeneous intermediate good sold in a competitive market. The intermediate good is produced with a constant returns technology represented by

$$Y_t = A_{c,t} \left(\left(n_{i,t}^d \right)^{(1-\sigma)} \left(n_{p,t}^d \right)^{\sigma} \right)^{1-\alpha-\nu} K_{t-1}^{\alpha} h_{e,t-1}^{\nu} \tag{3.5}$$

where $n_{x,t}^d$ is the the quantity of labor demanded, and K_{t-1} and $h_{e.t-1}$ are the quantities of capital and housing accumulated at the end of date $t-1$, respectively. The parameter σ determines the distribution of the wage share, and economic relevance, between patient and impatient households. Output is subject to TFP shocks which follow

$$\ln(A_{c,t}) = t\ln(1+\gamma_c) + \ln(v_{c,t}), \quad \ln(v_{c,t}) = \rho_c \ln(v_{c,t-1}) + u_{c,t}$$

where $u_{c,t}$ is a mean zero i.i.d. shock with variance σ_c^2. The stochastic stationary portion of the consumption good technology process is given by $v_{c,t}$, while γ_c is the deterministic growth rate of the productivity process.

The end of period capital stock K_t is composed of investment in new capital, I_t, and purchases of used, previously installed capital, $K_{b,t}$:

$$K_t = K_{b,t} + \left(1 - \frac{\Omega}{2}\left(\frac{I_t}{I_{t-1}} - G_I\right)^2\right) I_t \tag{3.6}$$

Entrepreneurs choose consumption $c_{e,t}$, housing stock $h_{e,t}$, used previously installed capital $K_{b,t}$, investment in new capital I_t, and loans $b_{e,t}$ to maximize

$$E_0 \sum_{t=0}^{\infty} (\beta_e G_c)^t \, \Gamma_e \ln(c_{e,t} - \epsilon_e c_{e,t-1}), \quad 0 < \beta_e < \beta_p \tag{3.7}$$

subject to the flow of funds constraint

$$c_{e,t} + q_t h_{e,t} + \frac{I_t}{A_{k,t}} + \frac{1 + r_{b,t-1}}{1+\pi_t} b_{e,t-1} + p_{k,t} K_{b,t} + w_{i,t} n_{i,t} + w_{p,t} n_{p,t} = b_{e,t} + q_t h_{e,t-1} + (1-\delta) p_{k,t} K_{t-1} + \frac{Y_t}{X_t} \tag{3.8}$$

where $\frac{1}{X_t} \equiv \frac{P_t^w}{P_t}$ is the relative price of the intermediate good and $p_{k,t}$ is the relative price of used capital. The relative price of investment is determined by investment-specific technological change $A_{k,t}$, which follows

$$\ln(A_{k,t}) = t\ln(1+\gamma_k) + \ln(v_{k,t}), \quad \ln(v_{k,t}) = \rho_k \ln(v_{k,t-1}) + u_{k,t}$$

where $u_{k,t}$ is a mean zero i.i.d. shock with variance σ_k^2. Capital depreciates at rate $\delta \in (0,1)$. As with impatient households, entrepreneurs cannot commit to repay their debt which limits the amount entrepreneurs can borrow each period to

$$b_{e,t}(1 + r_{b,t}) \leq m_{e,t}\left(E_t q_{t+1}(1 + \pi_{t+1})h_{e,t} + (1 - \delta)E_t p_{k,t+1}(1 + \pi_{t+1})K_t\right) \tag{3.9}$$

where $m_{e,t} \in (0,1)$ is an exogenous component of the LTV ratio on business loans and evolves according to

$$\ln(m_{e,t}) = (1 - \rho_e)\ln(m_e) + \rho_e \ln(m_{e,t-1}) + u_{e,t}$$

with $u_{e,t}$ being a mean zero, i.i.d. shock with variance σ_e^2. When the borrowing constraint binds, changes in expected future house prices and installed capital prices induce endogenous shifts in the demand for credit by entrepreneurs. Shocks to the LTV ratio exogenously shifts the demand for credit by entrepreneurs. This type of disturbance to credit conditions on the production-side of the economy has been utilized in estimated DSGE models by Liu et al. (2010) and Jermann and Quadrini (2011).

3.1.3 Financial Sector

The financial sector, which is operated by members of the patient household that are bankers, channels funds from patient households to impatient households and entrepreneurs. Bankers are themselves subject to a financial friction which builds on the framework of Gertler and Karadi (2011), the differences being the addition of multiple assets on the bank balance sheet - residential mortgages and business loans, and the addition of financial sector funding shocks. Denote by N_{jt} the amount of net worth that banker j has at the end of period t; D_{jt} the deposits the banker obtains from patient households, and B_{jit}, B_{jet} as the total amount of residential and business loans made by banker j, respectively, with $B_{jt} \equiv B_{jit} + B_{jet}$. The intermediary balance sheet is given by

$$B_{jt} = N_{jt} + D_{jt}$$

At period $t+1$, bankers pay the real amount $R_t \equiv \frac{1+r_t}{1+\pi_{t+1}}$ on deposits acquired at date t. Over time, the banker's net worth evolves as the difference between earnings on assets and interest payments on liabilities:

$$\begin{aligned} N_{jt+1} &= R_{b,t}\left(B_{jit} + B_{jet}\right) - R_t D_{jt} \\ &= \left(R_{b,t} - R_t\right)\left(B_{jit} + B_{jet}\right) + R_t N_{jt} \end{aligned}$$

where $R_{b,t} \equiv \frac{1+r_{b,t}}{1+\pi_{t+1}}$. Let $\beta_p^k \Gamma_{t,t+k}$ be the stochastic discount factor the banker applies at t to earnings at $t+k$. Since the banker will not fund assets with a discounted return less than the discounted cost of borrowing, then for the banker to be willing to operate in period t the following participation constraint must apply:

$$E_t \beta_p \Gamma_{t,t+1} \left(R_{b,t} - R_t\right) \geq 0 \tag{3.10}$$

In a frictionless funding market for bankers, the participation constraint holds with equality by necessity ($r_{b,t} = r_t$), otherwise the banker would demand an infinite amount of funds. With imperfect funding markets - in particular, a constraint on the amount a banker can borrow, the relation can hold with strict inequality in equilibrium. Provided the participation constraint (3.10) holds for any future horizon $t+k, k = 1, 2, \ldots$, then it pays for the banker to keep accumulating assets until exiting the industry. Accordingly, the banker's objective is to maximize expected career wealth, given by

$$\begin{aligned} V_{jt} &= \max \quad E_t \sum_{k=0}^{\infty} (1-\theta)\theta^k \beta_p^{k+1} \Gamma_{t,t+1+k} N_{t+1+k}^j \\ &= \max \quad E_t \sum_{k=0}^{\infty} (1-\theta)\theta^k \beta_p^{k+1} \Gamma_{t,t+1+k} \left[(R_{b,t+k} - R_{t+k}) \left(B_{jit+k} + B_{jet+k} \right) + R_{t+k} N_{jt+k} \right] \end{aligned}$$

To motivate a limit on borrowing by bankers, there is a moral hazard/costly enforcement problem: at the beginning of the period the banker can choose to divert the fraction λ_t of available funds from loans and instead transfer them back to the household of which he or she is a member. The cost to the banker is that the depositors can force the intermediary into bankruptcy and recover the remaining fraction $1 - \lambda_t$ of assets. The fraction λ_t is exogenously determined and follows

$$\ln(\lambda_t) = (1 - \rho_\lambda) \ln(\lambda) + \rho_\lambda \ln(\lambda_{t-1}) + u_{\lambda,t}$$

where $u_{\lambda,t}$ is an i.i.d. shock with zero mean and variance σ_λ^2.

In the event of bankruptcy depositors receive the remaining fraction of assets only at the end of the period, with no further opportunity to invest. For patient households to be willing to supply funds to the banker, the following incentive constraint must be satisfied:

$$V_{jt} \geq \lambda_t \left(B_{jit} + B_{jet} \right)$$

In Appendix D I show that V_{jt} can be expressed as

$$V_{jt} = \vartheta_t B_{jt} + \eta_t N_{jt}$$

where

$$\vartheta_t = E_t\left[(1-\theta)\beta_p\Gamma_{t,t+1}\left(R_{b,t}-R_t\right)+\theta\beta_p\Gamma_{t,t+1}x_{t,t+1}\vartheta_{t+1}\right] \tag{3.11}$$

$$\eta_t = 1-\theta+\theta\beta_p E_t\Gamma_{t,t+1}z_{t,t+1}\eta_{t+1} \tag{3.12}$$

$$x_{t,t+i} \equiv \frac{B_{jt+i}}{B_{jt}}, \quad z_{t,t+i} \equiv \frac{N_{jt+i}}{N_{jt}}$$

The expressions ϑ_t and η_t represent the marginal returns to participating in the financial sector along two dimensions: ϑ_t is the expected discounted marginal gain to the banker of expanding assets, holding net worth N_{jt} constant, while η_t is the expected discounted value of additional net worth, holding assets constant.

The incentive constraint can now be expressed as

$$\eta_t N_{jt} + \vartheta_t B_{jt} \geq \lambda_t B_{jt}$$

In Appendix D I show that the incentive constraint binds in equilibrium, yielding

$$B_{jt} = \frac{\eta_t}{\lambda_t - \vartheta_t}N_{jt}$$

Taking leverage to be the ratio of total assets to total equity, then the leverage of banker j is

$$\phi_t \equiv \frac{\eta_t}{\lambda_t - \vartheta_t} \tag{3.13}$$

which is composed of an endogenous component (η_t, ϑ_t) and an exogenous component

(λ_t). Bank net worth can now be expressed as

$$N_{jt+1} = \left[\left(R_{b,t} - R_t \right) \phi_t + R_t \right] N_{jt} \tag{3.14}$$

With no idiosyncratic shocks in the financial sector, I focus on an equilibrium with symmetric balance sheets across bankers. In this case, aggregating across individual demands for deposits yields

$$B_t = \phi_t N_t \tag{3.15}$$

$$D_t = B_t - N_t = (\phi_t - 1) N_t \tag{3.16}$$

where B_t, D_t and N_t are aggregate financial sector assets, deposits, and net worth, respectively. Combining (3.13) with (3.15) forms an upward-sloping supply of loanable funds in the lending rate $r_{b,t}$. Similarly, combining (3.13) and (3.16) forms a downward-sloping demand for deposits in r_t.

The evolution of net worth N_t follows from the accounting identity that it is the sum of net worth of existing bankers, N_{et}, and the net worth of new bankers, N_{nt}:

$$N_t = N_{et} + N_{nt}$$

Since the fraction θ of bankers at t were also bankers at $t-1$, N_{et} is given by

$$N_{et} = \theta z_{t-1,t} N_{t-1}$$

where

$$z_{t,t+1} = (R_{b,t} - R_t)\phi_t + R_t \tag{3.17}$$

For new bankers, the household transfers the fraction $\frac{\omega}{1-\theta}$ of total final period assets $(1-\theta)B_{t-1}$ of exiting bankers. Thus, $N_{nt} = \omega\frac{B_{t-1}}{1+\pi_t}$ so N_t evolves according to

$$N_t = \theta z_{t-1,t}N_{t-1} + \omega\frac{B_{t-1}}{1+\pi_t} \tag{3.18}$$

What is a financial sector funding shock?

Financial sector funding shocks are shocks to the banker diversion capability λ_t, and induce shifts in the supply of credit. A positive shock to the diversion capability λ_t increases the incentive to exit the financial sector through a higher return from diverting assets. Because of the binding incentive constraint, the returns to participating in the financial sector, and not divert assets, must rise. In equilibrium, the returns from not diverting rises through a contraction in leverage, i.e., a contraction in the supply of credit. A contraction in the supply of credit forces the lending-deposit spread higher, which increases the returns to participating through ϑ_t. Thus, a positive shock to λ_t constitutes a negative financial sector funding shock.

The banker diversion capability λ_t could be thought of as a measure of the complexity of financial assets held by the banker (from the perspective of the depositor). The higher the degree of complexity, the easier it is for bankers to divert resources and subsequently the tighter is the borrowing constraint faced by bankers. Green and Wachter (2005) and Gorton (2010) discusses how securitization can reduce the complexity of mortgage loans to potential investors, which can lead to an increase in the supply of credit as investors find it easier to evaluate the asset. Simsek and Caballero (2011) provide a model where shocks to complexity induce contractions in the supply of credit as potential investors become unable to evaluate assets.

Alternatively, Gorton (2010) argues that the legal structure of Special Purpose Vehicles, the legal entities through which securitized assets must be passed through from origination to sale, effectively reduced moral hazard problems between managers of MBIs and depositors/investors by limiting the amount of discretion available to financial managers. In this more direct interpretation of λ_t, financial innovation and deregulation encouraging securitization is captured through a decrease in λ_t, leading to an increase in the supply of credit through higher leverage. Gorton also argues that amendments to the U.S. Bankruptcy Code in the 1980s and later in 2005 made it harder for MBIs to divert assets through bankruptcy proceedings. In terms of the model, a change in bankruptcy law making it harder to divert assets would also imply an increase in the supply of credit through a decline in λ_t.

In Chapter 4.1 I provide reduced form evidence to evaluate these two interpretations of λ_t.

3.1.4 Final Goods Producers

Following Bernanke et al. (1999), nominal rigidities enter the economy through a continuum of monopolistic retailers (owned by patient households) who purchase the intermediate good from entrepreneurs at relative price $\frac{1}{X_t}$, costlessly differentiate it, then resell the differentiated goods in the final goods market. Retailers are subject to a Calvo price-setting rigidity, with $\zeta \in (0, 1)$ denoting the probability that any given retailer is unable to optimally reset her price in period t. Firms unable to optimally reset prices in period t index their date t price according to the previous inflation rate with elasticity ι. These assumptions lead to a Phillips curve of the form

$$\ln(\pi_t) - \iota \ln(\pi_{t-1}) = \beta_p G_c \left(E_t \ln(\pi_{t+1}) - \iota \ln(\pi_t)\right) - \epsilon_\pi \ln\left(\frac{X_t}{X}\right) + u_{\pi,t}$$

where $\epsilon_\pi = \frac{(1-\zeta)(1-\beta_p G_c \zeta)}{\zeta}$ and $u_{\pi,t}$ is a mean-zero, i.i.d. cost-push shock with variance σ_π^2.

3.1.5 Monetary Policy and Market Clearing Conditions

Monetary policy is conducted according to a Taylor rule of the form

$$1 + r_t = (1 + r_{t-1})^{\rho_r} \left((1 + \pi_t)^{\rho_\pi} \left(\frac{Y_t}{G_c Y_{t-1}}\right)^{r_Y} (1 + r)\right)^{1-\rho_r} \frac{u_{r,t}}{s_t}$$

where $u_{r,t}$ is a mean-zero, i.i.d. policy shock with variance σ_r^2 and s_t is an AR(1) process with mean zero i.i.d. shocks capturing persistent deviations of inflation from its steady state level, as in Iacoviello and Neri (2009).

The market clearing conditions consist of those for the goods market

$$Y_t = c_{i,t} + c_{p,t} + c_{e,t} + \frac{I_t}{A_{k,t}} \tag{3.19}$$

labor market

$$n_{i,t}^d = n_{i,t}, \quad n_{p,t}^d = n_{p,t} \tag{3.20}$$

used (previously installed) capital market

$$K_{b,t} = (1 - \delta) K_{t-1} \tag{3.21}$$

financial markets

$$B_{e,t} = b_{e,t}, \quad B_{i,t} = b_{i,t}, \quad D_t = d_t \tag{3.22}$$

and housing market

$$h_{i,t} + h_{p,t} + h_{e,t} = H_t \tag{3.23}$$

The supply of housing is given by H_t, and is exogenous. Iacoviello and Neri (2009) find differences in the long run technological growth rates of the housing and non-housing sectors to be an important factor in explaining the trend growth of real house prices. To allow for this characteristic without adding the complexity of residential investment and intersectoral labor supply decisions, I allow the supply of housing H_t to grow deterministically at rate $1 + \gamma_h$. Appendix D contains the full set of equilibrium conditions and stationary-inducing transformation of the model. Along the balanced growth path, aggregate consumption, investment, house prices, and the housing stock grow at rates

$$G_c = ((1 + \gamma_k)^{\alpha}(1 + \gamma_h)^{\nu}(1 + \gamma_c))^{\frac{1}{1-\alpha}}$$

$$G_I = G_k = (1 + \gamma_k)G_c$$

$$G_q = (1 + \gamma_h)^{-1} G_c$$

$$G_h = 1 + \gamma_h$$

Labor supply, interest rates, inflation, and leverage are stationary in the untransformed model. All remaining variables grow at the rate of consumption G_c. With the structural model in hand, the next section discusses the method used for taking the model to the data.

3.2 Estimation

The parameters of the model are estimated using Bayesian methods.[1] First, the model is linearized around the zero-inflation deterministic steady state along the balanced growth path. In the steady state, the borrowing constraints of impatient households and entrepreneurs bind as does the incentive constraint of the financial sector. These constraints bind in the linearized model, and in subsequent simulations the equilibrium conditions which characterize binding constraints are verified to hold.

Second, using the state space representation of the linearized model, the likelihood function is computed using the Kalman filter. Combining the likelihood function with prior distributions for the parameters, posterior distributions are estimated using the Metropolis-Hastings algorithm.

3.2.1 Data

The data is plotted in Figure C.5. The sample uses quarterly U.S. data from 1985.Q1-2010.Q4, which focuses on the period in which MBIs have played an increasingly important role in the mortgage market. Eight data series are used for estimation: personal consumption expenditures; business fixed investment; real wages and hours in the non-farm,

[1]See Sungbae and Schorfheide (2007) for a review of Bayesian estimation in DSGE models.

non-construction sector; real house prices; credit market lending in mortgages and business loans; and security broker-dealer leverage. Mortgage lending is given by the amount of outstanding residential mortgages. Business loans are credit market instruments held by all non-farm, non-financial corporate and non-corporate businesses. Broker-dealer leverage is the ratio of total financial assets to equity. All credit market and broker-dealer data is taken from the Flow of Funds.

Leverage is chosen to summarize MBI behavior for two reasons: (1) it is a reliable indicator of financial cycles, and (2) it can identify a housing demand shock from a shock originating in the financial sector.[2] The focus on security broker-dealers, as opposed to using aggregate data across multiple types of intermediaries, is to avoid the distortion of the true leverage of an intermediary which results from aggregating balance sheets and double-counting cross positions held by different types of financial firms - see Adrian and Shin (2010a). Broker-dealers, which by definition are any financial institution which buys and sells securities on behalf of its clients or on its own account, include a large swath of MBIs, including all the major investment banks which existed over the sample period.

Appendix A contains a detailed description of the data. As in Iacoviello and Neri (2009), I remove the level and keep the trend in the data used in the estimation. Due to the large divergence in real wage growth and consumption growth over the sample period and citing the discussion of the mismeasurement of wages in Sullivan (1997), I allow for measurement error in wages. The measurement equations are in Appendix D.

[2]See Reinhart and Rogoff (2009); Adrian and Shin (2009); Taylor and Schularick (2009); Adrian and Shin (2010b), Genakoplos (2009), and Owsley (2011).

3.2.2 Calibrated Parameters

A subset of the model parameters are calibrated because they are either difficult to estimate or are better identified by using other information. I calibrate the discount factors, depreciation rate, factor shares, banker transition probability, persistence of the inflation objective shock, steady state values of the markup, utility weights on housing, LTV ratios, and banker diversion capability. Table B.1 summarizes the calibrated values. Table B.2 lists the moments used for the calibration.

Beginning with parameters that pin down financial market moments, the patient household discount factor determines the steady state deposit rate. I set β_p to 0.9925 in order to match an annual return of 3%. Given the steady state deposit rate, I fix the steady state lending spread $r_b - r = 0.0042$ in order to match an annual 1.7% spread between the 30-year fixed mortgage rate and 10-year T-bill over the sample period. Steady state financial sector leverage is set to 21, which matches that in the data for security broker-dealers over the sample period. The banker transition probability θ is set to 0.9, implying an average tenure in a specific intermediary of three years, which is consistent with survey data on broker-dealers.[3] Given a value for the lending spread, patient household discount factor, banker transition probability θ, and leverage, the steady state banker diversion parameter λ is determined.

Moving on to the parameters which pin down housing market moments, the housing utility scaling factors, j_i and j_p, are set to 1.87 and 0.22, respectively. These values enable the model to match a household real estate wealth-to-output ratio of around 1.7 and a mortgage debt-to-output ratio of 0.64.[4] The steady state LTV ratios for mortgages and business loans are set to 0.85 and 0.55, respectively, which match averages in the U.S. and

[3] http://www.advisorone.com/2011/02/15/pershing-study-forecasts-shortage-of-bd-reps

[4] To be consistent with the model, output is defined as the sum of consumption and business fixed investment.

other economies with liberalized credit markets over the sample period.[5]

Parameters which pin down production sector moments are the depreciation rate, capital and housing share. These are set to 0.03, 0.325, and 0.035, respectively. With these values, the steady state attains an investment share of output of 17% and a business sector real estate wealth-to-output ratio of 1.3, as in the data.[6]

Because the steady state markup is not well identified in the model equations, I set the steady state markup to 1.15, which is consistent with Iacoviello and Neri (2009) and other standard calibrations of DSGE models. Like in the Iacoviello and Neri estimation, the autocorrelation of the inflation persistence shock ρ_s is not well identified in estimations. Following Iacoviello and Neri, I set this value to 0.975, implying an annual autocorrelation of trend inflation around 0.9.

3.2.3 Priors

Prior distributions are detailed in Table B.3. Overall, the priors are consistent with previous studies - in particular, Iacoviello and Neri (2009), Smets and Wouters (2007), and Justiniano et al. (2011).

For the exogenous processes, persistence is beta distributed, with mean and standard deviation 0.80 and 0.10, respectively. Standard errors for the shocks follow inverse gamma distributions, and are scaled as in Walentin (2011) to aid in the computation of the mode. Scaling factors are chosen to match the orders of magnitude of shock standard deviations in Iacoviello and Neri (2009). Otherwise, no further stance on the relative volatility of each shock is taken.

[5] See Tsatsaronis and Zhu (2004), Kariner (2009), and Green and Wachter (2005).

[6] Real estate ratios were calculated using U.S. Federal Reserve Flow of Funds tables B.100, B.102 and B.103.

For the parameters governing the degree of nominal and real rigidities, the prior mean for the average duration of prices is set to around three quarters. The number of firms indexing prices to inflation is centered at 50%. Households have stronger prior habits in consumption than entrepreneurs, with habit persistence centered at 0.80 and 0.50, respectively. Based on Christiano et al. (2005), the adjustment cost parameters, Ω and ϕ_p^h, follow a gamma distribution with mean 2.1. In the baseline estimation, impatient households do not incur housing adjustment costs. In Chapter 3.3 I show that adding housing adjustment costs for impatient households results in a deterioration of the marginal likelihood of the model.

The remaining parameters concern technology, preferences, and policy. Deterministic growth rates of the technological processes, γ_c, γ_k, and γ_h, follow normal distributions with relatively tight priors centered at their respective counterparts in the sample data. The sample technological process growth rates are backed out using sample growth rates in consumption, investment, and house prices together with the expressions for the model trends. The elasticity of labor supply for households, determined by χ_i, χ_p are both gamma distributed with a mean of 2. The prior mean of the labor income share of patient households is set to 0.65, following Iacoviello and Neri (2009). The Taylor rule parameters ρ_y, ρ_r and ρ_π are centered at $0, 0.75$, and 1.2.

3.2.4 Posteriors

Posterior means, standard deviations, and percentile intervals are summarized in Table B.3. Details on the estimation procedure, including convergence diagnostics and plots of the posterior distributions, are in Appendix D.[7]

[7] Draws from the posterior distribution of the parameters are obtained using the random walk version of the Metropolis algorithm. Tables and figures are based on two chains, each with 350,000 draws. The jump distribution was chosen to be normal with covariance matrix equal to the Hessian of the posterior density evaluated at the maximum. The scale factor was chosen to obtain an acceptance rate of about 29 percent.

At the posterior mean, the labor share of impatient households is 31%. Consumption habits are lower for entrepreneurs ($\epsilon_e = 0.41$) relative to patient households ($\epsilon_p = 0.48$) and impatient households ($\epsilon_i = 0.77$). The stronger habit persistence for impatient households could result from the fact that they face the poorest consumption smoothing possibilities, requiring a higher degree of habit persistence to reconcile the persistence of consumption in the data. For possibly a similar reason, impatient households have a lower labor supply elasticity than patient households (1.67 vs. 2.08). The posteriors of the adjustment cost parameters are relatively tight, with means lower than their prior ($\Omega = 1.06$ and $\phi_p^h = 0.06$).

The estimated technological parameters imply average annual growth rates of consumption, investment, and house prices of 2.2%, 1.2%, and 0.55%, respectively, which is close in line with the sample. The estimated trends and percentile intervals are plotted in Figure C.6, and are based on $1,000$ draws from the posterior.

For the remaining parameters, prices are optimally reset with a mean frequency of about seven quarters. There is almost full price indexation at the mean ($\iota = 0.96$). The monetary policy reaction coefficients are consistent with previous estimated New Keynesian models, with a high degree of interest rate smoothing ($\rho_r = 0.72$), and a response to inflation approximately six-times as large as that to output. The estimated exogenous process are generally very persistent. The housing demand, entrepreneur credit, and financial funding shock have autocorrelation coefficients of $0.99, 0.98$, and 0.91, respectively.

Convergence was assessed according to the Brooks-Gelman diagnostics.

3.3 Properties of the Model

3.3.1 Impulse Responses

Financial Sector Funding Shock

Figure C.7 displays the median quarterly impulse responses to a negative one standard deviation financial sector funding shock. A negative funding shock is a positive shock to the banker's diversion capability λ_t, which on impact increases the incentive to exit the financial sector through a higher return from diverting assets. Because of the binding incentive constraint, the returns to participating in the financial sector, and not divert assets, must rise. In equilibrium, the returns from not diverting rises through a contraction in leverage, i.e., a contraction in the supply of credit. A contraction in the supply of credit forces the lending-deposit spread higher, which increases the returns to participating through a higher return on lending (ϑ_t increases) and net worth (η_t increases). The contraction in the supply of credit reduces consumption, investment, and housing demand by impatient households and entrepreneurs. With falling aggregate demand, inflation falls and the central bank responds by lowering the deposit rate. The fall in the deposit rate attenuates the equilibrium rise in the lending rate, however borrowers still face oppressive credit burdens due to debt deflation.

The quantitative effect of the funding shock on economic activity is felt primarily in investment. At its peak response, investment falls by 3.5%, and stays below its steady state value for over two years. Consumption falls by less (.25% at its peak response), but is more persistent, staying below its long run average for over five years. On the financial side of the economy, the funding shock has asymmetric effects on lending: mortgage loans fall by 6% at their peak response while business loans fall by 2.5%. Compared to entrepreneurs, households have fewer assets to use as collateral and have higher consumption habits, making falling house prices and debt deflation induce a larger contraction in borrowing. Leverage falls by 8% at its peak response, the largest of any of the variables, and takes nearly three years to hit bottom.

The funding shock induces a rich interaction between financial sector leverage, collateral effects from house prices, and debt deflation. To understand the contribution of each of these effects, Figure C.8 breaks down the impulse responses by shutting down these channels one at a time.

The debt deflation effect (black line) plays the largest quantitative role in the funding shock. In this interaction, the funding shock contracts the supply of credit, forcing a decline in inflation through reduced aggregate demand. Lower inflation increases the real debt burdens of impatient households and entrepreneurs, which puts further downward pressure on aggregate demand.

The second most important interaction comes from the collateral effect of house prices on the demand for credit (red line). In this interaction, the contraction in the supply of credit reduces the demand for housing by impatient households and entrepreneurs. Lower house prices decrease credit demand through the collateral effect, which coupled with the contraction in credit supply, results in a large equilibrium decline in credit. In contrast, with exogenous borrowing limits that do not depend on house prices, there is only a small decline in lending. The decline in lending is entirely from the decline in credit supply (note the much larger increase in the spread relative to the baseline model).

The housing adjustment cost faced by patient households also plays a quantitative role in the funding shock, particularly with respect to house prices (green line). Since the contraction in credit brought about by the funding shock reduces housing demand among impatient households and entrepreneurs, patient households must buy up the excess in equilibrium. Faced with an adjustment cost in housing, house prices must fall by more for the market to clear. Through collateral and debt deflation effects, the further fall in house prices propagates the shock across all macro and credit variables.

Housing Demand Shock

Figure C.9 displays the median quarterly impulse responses to a negative one standard deviation housing demand shock. The decline in housing demand depresses house prices, forcing declines in the demand for credit by impatient households and entrepreneurs through the collateral effect. Tighter credit limits force declines in consumption, investment, and output. With the demand for final goods lower, inflation falls, prompting a decline in the deposit rate by the central bank and further tightening of credit conditions through debt deflation.

On impact of the shock leverage falls, but then rises persistently. To understand this, first consider the initial period of the shock. Since financial sector net worth is determined by the ex-post profitability of lending (which itself is only affected by inflation), then leverage is almost entirely determined by total lending *in the period of the shock*. Thus, the decline in the demand for credit lowers leverage initially. From the second period onward, net worth drops dramatically through both lower spreads and lower lending. The loss of net worth increases the marginal returns to participating in the financial sector - participating allows the chance to recover lost net worth. With a smaller incentive to divert funds, the funding market for bankers improves and leverage is allowed to rise. The rise in leverage after a negative housing demand shock is consistent with the response to an identified housing demand shock in a monetary VAR with house prices and leverage (Owsley, 2011).

Compared to the funding shock, the quantitative effects are slightly smaller for consumption and half as large for investment. For financial variables, the decline in equilibrium business loans is also about half as large as with the funding shock. The difference is due to the nature of the shock: a funding shock is initially a contraction in the supply of credit across both mortgages and business loans. The contraction in the supply of credit induces an endogenous contraction in the demand for credit through collateral effects and debt deflation. On the other hand, the housing demand shock is initially a decline in the demand for credit by households and entrepreneurs through collateral effects, debt deflation, and lower aggregate demand. The decline in the profitability of lending induces an endogenous **increase** in the supply of credit through the desire for bankers to recover lost net worth, attenuating the contraction in credit demand by entrepreneurs which leads to an overall smaller quantitative effect on macro variables.

Remaining Shocks

Figure C.10 displays the median quarterly impulse responses to a negative one standard deviation entrepreneur credit shock. Figure C.11 displays the median quarterly impulse responses to a contractionary monetary policy shock and Figure C.12 displays the responses to a negative TFP shock. Responses to the remaining shocks are in Appendix D. Responses for these standard business cycle model shocks with respect to consumption, business fixed investment, inflation, and house prices are consistent with those in Iacoviello and Neri (2009), Jermann and Quadrini (2011), and Smets and Wouters (2007).

The qualitative response of leverage to the remaining shocks mimics the response to the housing demand shock: leverage falls initially before persistently rising. This is because all the other shocks in the model feature a shift in the demand for credit which outweighs shifts in credit supply, as in the housing demand shock. A negative credit demand shock reduces banker profitability, increasing the returns for bankers to continue to participate in the financial sector to recover lost net worth. Better aligned incentives result in a loosening of their endogenous funding constraint, increasing leverage. Because in these cases a contraction in credit demand is met with an increase in credit supply, the endogenous leverage constraint faced by bankers acts to dampen outside macro shocks. Much more will be said about the ability of endogenous MBI leverage to be a propagation mechanism of business cycles in Chapter 4.2.

In summary, the financial funding, housing demand, and entrepreneur credit shock all induce positive co-movement between macro variables, house prices, and credit. Of these three shocks, the financial funding shock induces the largest quantitative response among the variables. The key distinguishing feature among these shocks is the response to financial sector leverage. The financial funding shock is the only shock in the model which can produce persistent positive co-movement among leverage, macro variables, house prices, and credit. Armed with an understanding of how the model works, I now move to assessing the model's performance in matching business cycle moments.

3.3.2 Cyclical Properties

Table B.4 contains data and model-generated correlations with respect to macro and financial variables.[8] Most of the 97.5% intervals generated by the model overlap those of the data - the only exception being the correlation between output and house prices. The model does a particularly good job in matching the correlations among macro variables and that between house prices and mortgage credit. In general, the model tends to deliver a stronger correlation between macroeconomic and financial variables than is suggested by the data. The wide variability in the correlation between output and leverage is not just a model phenomenon: the pre-crisis correlation in the data is around -0.10, while the

[8]The statistics were computed by taking $1,000$ draws from the posterior distribution and, for each draw, simulating 100 artificial time series of a length equal to that in the data. The business cycle component of each simulated series is extracted using the HP filter with smoothing parameter set to $1,600$.

post-crisis correlation is 0.02. No other correlations listed in Table B.4 change significantly either in sign or magnitude across the pre and post-crisis period.

The empirical measure used in the estimation for tightness in the supply of credit is broker-dealer leverage. An alternative approach to measure shifts in credit supply is to use a measure of interest rate spreads.[9] To get a sense of how well the model can capture changes in interest rate spreads when using only broker-dealer leverage in the estimation, I compare the ex post lending-deposit spread based on the smoothed structural shocks to Senior Loan Officer Survey (SLOS) data compiled by the Federal Reserve. Specifically, the blue line in the top panel of Figure C.14 plots the net percentage of commercial bankers increasing their lending rates to firms over their own cost of funds. A value greater than zero indicates a majority of respondents are increasing their own lending-deposit spread. A survey response that trends upward indicates increasing spreads are becoming more pervasive throughout the economy. The results from this survey give a broad indication of the direction of spreads received by financial institutions. Since other questions in the survey account for tightening loan standards, the survey response on spreads could be considered as an indicator of spread movements dictated by shifts in credit demand and supply independent of default risk, which is closest to the reason why the spread in the model fluctuates. The green line in the plot takes on a value of either 100 or -100. A value of 100 indicates the ex post lending deposit spread is greater than its steady state value, while a value of -100 indicates it is below its steady state value.

Generally the ex post spread in the model is above its steady state value whenever there is an upward trend in the net percentage of bankers increasing spreads. The model especially delivers an increasing spread during all three recessions and during the LTCM crisis. Thus, using leverage of broker-dealers, together with credit market and macroeconomic data in the estimation of the model, produces an ex posting lending-deposit spread

[9]For examples, see De Graeve (2008), Gilchrist and Zakrajsek (2011a), Gilchrist and Zakrajsek (2011b), and Christiano et al. (2009).

which has dynamics generally consistent with the dynamics of spreads indicated by the SLOS.

3.3.3 Model Sensitivity: which frictions are empirically important?

The importance of the real and nominal rigidities in bringing the model closer to the data is documented in Table B.5. Each column presents the marginal likelihood when removing/dramatically reducing one friction.[10] The most important rigidity in the model (in terms of the marginal likelihood) is that of prices - reducing the Calvo probability to $\zeta = 0.1$ decreases the marginal likelihood by 43%. Investment adjustment costs are the most costly real rigidity to eliminate - the marginal likelihood falls by 8% when removing it. Just as important is the *absence* of housing adjustment costs for impatient households: allowing for these causes the marginal likelihood to deteriorate by 8%. Of less importance, eliminating consumption habits or inflation indexation results in a small deterioration of the marginal likelihood of around 4%. Allowing for sticky wages has virtually no effect on the likelihood (a loss of 1%).

In Appendix D I document the sensitivity of the model parameters to the real and nominal rigidities in the model. Overall, the estimated parameters are robust to changes in the frictions one by one. Eliminating frictions changes a small subset of parameters in ways that compensate for the loss of the friction.

[10]The marginal likelihood is based on the Laplace approximation. See DeJong and Dave (2007) for a formal introduction and comparison of alternative methods to compute the marginal likelihood of a DSGE model.

CHAPTER 4

EMPIRICAL ANALYSIS

4.1 Housing and MBIs: a source of business cycles

With the estimated model in hand, I now focus on analyzing the role of the housing market and MBIs in the cycle. In this subchapter, the focus is on the importance of housing demand shocks and financial funding shocks in driving business cycle fluctuations. Particular importance is placed on understanding their role in the Great Recession.

4.1.1 Variance Decomposition

Table B.6 contains the average median forecast error variance decomposition across 1, 4, and 8 quarter horizons.[1] Fluctuations in both macro and financial variables are largely driven by macro shocks: macro shocks in the aggregate capture anywhere from 56% (house prices) to 93% (consumption) of business cycle movements. Macro shocks have a pervasive influence across both real and financial variables. Financial funding and housing demand shocks, on the other hand, are not nearly as important in accounting for fluctuations in consumption (4%) and investment (17%) as they are in accounting for fluctuations in financial variables and house prices (19 – 42%). Having said that, financial funding and housing demand shocks are by no means irrelevant. Combined, both shocks account for at least 15% of fluctuations in investment, the t-bill rate, house prices, credit, and broker-dealer leverage.

In relative terms, financial funding shocks are more important than housing demand shocks. Funding shocks account for nearly five-times the forecast error variance of in-

[1] The values reported in the table are based on 1,000 draws from the posterior distribution.

vestment as housing demand shocks do (14% vs 3%), and twice that for consumption (3% vs. 1.5%) and the t-bill rate. Among non-macro variables, funding and housing demand shocks each account for 9% of leverage fluctuations, but funding shocks are more important in accounting for fluctuations in business loans (19% vs. 2%). Housing demand shocks are significant in explaining only housing market movements, accounting for 21% of mortgage fluctuations and 35% of house price fluctuations. Still, the funding shock accounts for a respectable 10% and 7% of fluctuations in mortgages and house prices, respectively. Housing demand shocks are much like entrepreneur credit shocks in terms of their explanatory power in fluctuations. Although the entrepreneur credit shock accounts for 19% of fluctuations in business loans, it accounts for no more than 6% of the fluctuations of any other variable.

The funding, housing demand, and entrepreneur credit shock are all relatively unimportant in explaining consumption. This is a common feature among estimated DSGE models with a housing demand shock or entrepreneur credit shock - see Iacoviello and Neri (2009), Walentin (2011), and Jermann and Quadrini (2011). Justiniano et al. (2011) also find that their shock to the marginal efficiency of investment is important in investment and output fluctuations but unimportant in consumption fluctuations. Insight into this property is gained from examining Figure C.13. Here I plot the consumption response to the financial, housing demand, and entrepreneur credit shocks against the response to a TFP shock, which is one of the most important shocks in driving consumption fluctuations. What distinguishes these shocks from the TFP shock is that they are essentially redistributive. A (negative) financial funding shock prevents additional consumption by impatient households and entrepreneurs, but allows for more consumption by patient households since they, by construction, do not lend as much to bankers. Similarly, housing demand and entrepreneur credit shocks reduce consumption by borrowers through collateral effects, but since the reduced consumption comes mostly through less borrowing, patient households need not save as much and can increase their consumption. Thus all three of these shocks, because of their redistributive effects on consumption, imply a much smaller consumption response compared to a shock which unambiguously decreases consumption by all agents, such as a TFP shock.

4.1.2 Historical Decomposition

Financial funding and housing demand shocks over the sample

I now examine the importance of the estimated financial funding and housing demand shocks in explaining business cycle fluctuations observed in the sample, including the Great Recession. While the variance decomposition reveals that both of these shocks could play a nontrivial role in fluctuations, the large declines in consumption during the Great Recession suggest these shocks could not have been the only shocks which hit the economy. Once the role of housing demand and financial funding shocks has been disentangled, I will analyze the influence of other shocks in the Great Recession.

Financial funding shocks

Figure C.15 plots the estimated exogenous processes over the observed sample period. The banker diversion capability λ_t is determined by financial funding shocks. There is a clear underlying downward trend in λ_t over the entire sample leading up to the Great Recession, indicating positive funding shocks which have loosened the borrowing conditions for broker-dealers have dominated during most of the sample. The largest funding shocks occurred after 2005: From 2005-2007, large positive funding shocks send λ_t downward at its fastest rate over the sample. There is an unprecedented large negative funding shock in late 2007, and subsequently further negative funding shocks throughout the recession and recovery period, resulting in a (at least temporary) reversal in λ_t and tightening of broker-dealer borrowing conditions.

Understanding what the funding shock is actually capturing is important to inspire confidence in the path it implies for macro and financial variables. To this end, the bottom two panels of Figure C.14 are plots of the estimated funding shock against the change in the average price of a 1-year credit-default swap (CDS) for the primary dealers, a subset of broker-dealers that serve as trading counterparties of the New York Fed in its implementation of monetary policy.[2] CDS only began being traded in the early 2000s. The price of a CDS reflects the willingness of the buyer to bear the risk of default by a primary dealer. Hence, changes in CDS prices reflect the ease to which MBIs can borrow. Overall, changes in CDS prices for primary dealers track funding shocks well. Funding shocks track the low/falling prices observed in the early to mid-2000s, the large, unprecedented spike in prices seen at the peak of the financial crisis, as well as the fall and slight rise observed after the crisis. The close alignment of funding shocks and CDS prices leading up to and during the Great Recession indicates that the financial funding shock is capturing changes in funding market conditions faced by MBIs.

Funding market conditions can also be influenced by regulation. Gorton (2010) argues that the most important necessary condition for sustained growth in MBI leverage is the regulatory protections afforded to holders of repos, which were the main contract used by MBIs to borrow. In 1984, an amendment to the 1978 Bankruptcy Code allowed any holder of a repo to carry out necessary seizures of collateral if the seller of the repo declared bankruptcy. While the initial provision in 1984 only included repos based on Treasuries, agencies, bank CDs, and bankers' acceptances, there was an additional reform passed in 2005 which extended the protections to any repo using stock, bond, mortgages, and other assets. These regulatory changes could rationalize the underlying downward trend in λ_t as well as the particular sharp fall in λ_t beginning in 2005. This is because the re-

[2] A list of the primary dealers and further information about them can be found at http://www.newyorkfed.org/markets/pridealers_current.html.

forms made it more difficult for sellers of repos to divert assets through costly bankruptcy procedures, which in terms of the model would directly imply a decline in λ_t.

With evidence that the estimated funding shock does reflect actual funding market conditions for MBIs, I now asses the role of funding shocks in observed fluctuations. Figure C.16 plots the implied path of variables **without** funding shocks (red line) against the data (black line). Large deviations between the data and what would have happened without funding shocks indicates that funding shocks were important.

Beginning with macro variables, the role of funding shocks in consumption has been much different than its role in investment. After the 1990 recession, funding shocks supported higher consumption, an effect which lasts throughout the rest of the sample. Rather than directly contributing to booms and busts in consumption, funding shocks have allowed for higher consumption in the presence of other shocks which are mostly responsible for its business cycle movements. On the contrary, funding shocks have played an important role in investment fluctuations, particularly in the downturn in investment before the 1990 recession, the boom in investment during the 1991-1993 period, and most of all, the boom in investment after the 2001 recession. The implied path of investment without funding shocks would completely miss the rise in investment from 2001-2007, and would also underpredict the fall in investment at the onset of the Great Recession.

Moving to non-macro variables, the role of funding shocks in house prices is somewhat between its role in investment and consumption. Beginning in the late 1990s, funding shocks contributed significantly to the early stages of the most recent housing boom. In the later stages of the boom and early part of the bust, funding shocks helped sustain house prices rather than drive house price changes. Funding shocks play a significant role in explaining the underlying persistent rise in broker-dealer leverage from the early 1990s, and in particular to the steepest rise in leverage occurring just before the crisis. However, abrupt changes in leverage, such as those experienced during the 2001 recession and financial crisis, are explained by macro shocks. Funding shocks are important in explaining credit movements, especially in expansionary phases of the business cycle, over the entire sample. Positive funding shocks were almost entirely driving the continued expansion in mortgage credit from 2006-2008 and fall at the onset of the Great Recession. Funding shocks become important in explaining the persistent low interest rates beginning in 2008 - without funding shocks, the t-bill rate rises rapidly from 2008 onwards.

Housing demand shocks

Housing demand shocks, summarized by the evolution of j_t in Figure C.15, have clearly become larger over the sample period, with the largest positive shocks occurring from 2000-2005 followed by unprecedented negative shocks. The pattern of j_t is similar to the estimated housing demand shock in Iacoviello and Neri (2009). Iacoviello and Neri attempt to explain innovations to housing preferences by mortgage market characteristics such as initial fees and charges for a mortgage, the share of subprime mortgage originations out of total originations, the after-tax mortgage rate, and other economic fundamentals not well captured in a stylized macro model. They find these fundamentals can only partially explain movements in housing preferences, leaving open the possibility of "animal spirits" as a driver of j_t.[3]

As suggested by the variance decomposition, the influence of housing demand shocks in macro fluctuations is smaller than that of funding shocks. Housing demand shocks play essentially no role in consumption fluctuations over the sample, but do play a nontrivial role in the initial uptick in investment after the 2001 recession as well as the slowdown in investment beginning in 2007. Housing demand shocks did positively contribute to the most recent housing boom around the peak of the boom and most significant of all,

[3]See (Akerlof and Shiller, 2009) for a specific application to the housing market.

in driving the collapse in house prices beginning in 2006.

In financial variables, housing demand shocks contribute significantly to the peak rise in leverage before the onset of the Great Recession as well as the peak, and subsequent fall, in mortgage loans from 2004-2010. Business loans are not driven by housing demand shocks. Housing demand shocks contribute to the rise in the t-bill rate beginning in 2004 as well as the drop in the t-bill rate after 2005, with little influence in the t-bill rate in previous business cycles.

Disentangling the Great Recession

Financial funding and housing demand shocks have had their most significant impact over the sample in the period surrounding the Great Recession. An unprecedented negative housing demand shock was responsible for the collapse in house prices and played a significant role in the contraction in mortgage lending. Financial funding shocks, after driving the credit expansion and initially mitigating the effects of negative housing demand shocks on credit, turned sharply negative. An unprecedented negative financial funding shock largely drove the drop in investment, credit and to a lesser extent, house prices.

However, these shocks do not explain the large drop in consumption leading up to and at the onset of the Great Recession nor do they explain the tepid recovery in consumption and investment from 2009-2011. With these features left to explain, I again turn to Figure C.15. Unique to the Great Recession is not only the unprecedented large negative financial funding and house demand shocks, but also unprecedented large negative TFP and cost-push shocks. Monetary policy shocks, both in the form of i.i.d. and inflation-targeting shocks, were large and expansionary at the onset of the Great Recession, but then turned large and contractionary beginning in late 2009. Also in 2009 was a large positive discount factor shock.

Another uncharacteristic feature of the Great Recession is a relative *easing* of credit conditions for entrepreneurs. From Figure C.15, $m_{e,t}$ rises from 2005 onwards and especially trends upward during the recession. In prior recessions, credit for entrepreneurs tightens before the recession and generally takes 2-3 years to recover. To investigate the extent to which the estimated entrepreneur credit shock accurately captures credit market dynamics faced by firms during the Great Recession, I compare the estimated shock to Senior Loan Officer Survey data from the Federal Reserve. The second panel of Figure C.14 plots the negative value of the entrepreneur credit shock against the net percentage of bankers tightening credit conditions for firms more than for mortgages. If anything, the estimated path for $m_{e,t}$ underpredicts the easing of business credit conditions during the Great Recession, as indicated by the SLOS.

Figures C.16-C.18 display the full historical decomposition of all the shocks, where each decomposition is the implied path of variables **without** the specified shock. Large deviations indicate the shock is important. The decline in consumption from 2006-2008 is almost entirely explained by negative technology shocks - in particular, negative TFP shocks which began hitting the economy in 2007 and 2008. Technology shocks, particularly TFP shocks, also played a role in the decline in investment and credit. The lack of a stronger recovery in consumption has been largely caused by negative cost-push shocks and positive discount factor shocks. Cost-push shocks have also played a role in the slow recovery of investment. Monetary policy shocks were stimulative for investment, credit, and house prices during the latter part of the recession but had little effect on consumption. In the recovery, monetary policy shocks have been at best neutral or contractionary. Looking at the t-bill rate explains why: from 2009 onwards, the presence of the zero lower bound has acted as contractionary monetary policy, keeping the t-bill rate higher than suggested by a Taylor Rule which responds only to output and inflation.

In summary, the Great Recession is marked by an unprecedented coincidence of large technology, financial funding, and housing demand shocks. Negative technology shocks began the initial downturn, affecting consumption mainly but eventually contributing to declines in credit. Housing demand shocks followed, causing a collapse in house prices and contributing to declines in investment and further contractions in mortgage credit. Financial funding shocks had been stimulative until 2007, mitigating the effects of negative technology and housing demand shocks on investment, credit, and leverage. But ultimately, large negative financial funding shocks dealt the final blow, causing significant further declines in investment and credit. Monetary policy, as reflected by the t-bill rate, appears to have responded to housing demand shocks first, followed by TFP and funding shocks. Funding shocks almost entirely account for interest rates being driven to the zero-lower bound. In the recovery, negative cost-push shocks and discount factor shocks have kept a lid on stronger gains in investment and consumption. Being constrained by the zero lower bound, monetary policy shocks have had a neutral or negative impact on macro variables and credit.

Comparison to Stock and Watson (2012)

Despite the gulf between the methodology used by Stock and Watson (2012) and myself, a strikingly similar conclusion about the Great Recession emerges: it was an unprecedented coincidence of large shocks, of which only some were financial oriented.

Stock and Watson study the causes of the Great Recession by using a dynamic factor model with 198 variables covering macro aggregates, employment, money and credit, house prices, inventories, interest rates and spreads, stock prices, exchange rates, and oil prices. There are six shocks identified: oil, monetary policy, productivity, uncertainty (captured through the VIX and an indicator of policy uncertainty), liquidity/financial risk, and fiscal policy. Stock and Watson identify the shocks through an instrumental variables technique (Mertens and Ravn, 2012), using as instruments estimated shocks from DSGE models and indicators of exogenous disturbances from other outside sources. Stock and Watson conclude that the Great Recession was caused by an unprecedented confluence of large shocks: an initial large oil shock, followed by multiple financial shocks. Shocks to policy uncertainty are blamed for the slow recovery in consumption, while monetary policy shocks have been neutral or contractionary.[4] Financial shocks are shown to have played a relatively small role in prior recessions. Stock and Watson are not the first to provide evidence that an oil shock was the initial trigger for the Great Recession. Hamilton (2009) shows through a careful analysis on consumption that had the oil price spike of 2007-2008 not occurred, then the starting date for the Great Recession would have been at least delayed several months.

Although the non-financial shocks which are important in the Stock and Watson analysis differ from those uncovered here, the distinction is more in name than in substance. First consider the discrepancy between the initial shocks leading to the Great Recession: Stock and Watson (together with Hamilton) provide evidence it was a series of oil price shocks while I find it was a series of negative supply shocks in the form of TFP shocks.[5] Peersman and Stevens (2010) estimate a multi-country DSGE model with endogenous oil prices and use for oil in consumption, production, and investment. They decompose oil supply shocks in the form of (1) shocks to capacity; (2) the market power of oil producing countries; and (3) productivity in oil-bearing reserves, from oil demand shocks in the form of (1) own-market demand (speculation), and (2) other macroeconomic shocks from the domestic and foreign economy. Peersman and Stevens find that all oil supply shocks and own-market demand shocks have the same dynamics as TFP shocks. Without explicitly including oil in my model, the negative oil price shocks recovered in Stock and

[4] Gali et al. (2012) also finds monetary policy to have been contractionary throughout the recovery and attributes the finding to the zero-lower-bound constraint on nominal interest rates.

[5] Jermann and Quadrini (2011) also find that a significant portion of the Great Recession was caused by negative TFP shocks.

Watson are likely being recorded as TFP shocks in my decomposition.

The other difference between my decomposition and that of Stock and Watson is in the explanation of the slow recovery. Stock and Watson find shocks to policy uncertainty, while I find the explanation to lie in discount factor shocks. Villaverde et al. (2011) builds a New Keynesian model with fiscal policy uncertainty shocks, and finds the response to investment and output to mimic those of a discount factor shock. To the extent that increased policy uncertainty causes households and firms to restrain from spending until the future path of economic policy is more certain, the discount factor shock in my model would deliver a similar implication as policy uncertainty shocks found in the Stock and Watson analysis.

4.1.3 Summary

Financial funding shocks are more important sources of business cycle fluctuations than housing demand shocks. At business cycle frequencies, funding shocks account for as much fluctuations in investment, house prices, credit, the t-bill rate, and broker-dealer leverage as half the other shocks in the model. Funding shocks have played a role in driving investment and credit fluctuations over the entire sample, with their largest influence beginning in the late 1990s. From this time through 2011, funding shocks propped up consumption in the face of mostly negative technology shocks rather than drive its ups and downs at business cycle frequencies. The biggest influence of funding shocks were in driving the initial boom in housing prices after the 2001 recession, the large boom and bust in investment from 2002-2007, as well as the expansion in credit and leverage - particularly from 2005-2007.

Housing demand shocks, on the other hand, mainly drive own-market fluctuations in house prices and mortgage loans. Housing demand shocks are unimportant in understanding fluctuations of macro and financial variables as well as house prices for most of the sample. Housing demand shocks drove the most recent housing boom only late in its life, from 2004-2006. During this time, housing demand shocks contributed to rising broker-dealer leverage and also played a role in the expansion of investment, but did not affect consumption or business loans. Unprecedented negative housing demand shocks were responsible for the housing collapse and played a role in the contraction of mortgage credit at the onset of the Great Recession.

4.2 Housing and MBIs: propagating business cycles

I now move to analyze the extent to which housing and MBIs can *propagate* shocks which originate from other parts of the economy. To frame the analysis, I will exploit two well-documented facts about housing and MBIs: (1) since the early 1980s, MBI leverage has increased, and with higher leverage their share of total mortgage credit provided in the economy has also risen (see Figure C.4); (2) The maximum LTV ratio for mortgage loans has increased over time (Duca et al., 2011). If these long run changes in mortgage finance and MBIs alters the transmission mechanism of macro shocks, then housing and MBIs matter in understanding business cycles irrespective of the importance of their own shocks.

4.2.1 Effects of higher long-run MBI leverage

Leverage for MBIs has steadily increased since the 1980s: average MBI leverage was 15 in 1985 and 25 in 2007. Looking at the evolution of leverage in Figure C.5 as well as the estimated path for λ_t (Figure C.15) suggests an underlying low frequency structural change for MBIs that is unrelated to the business cycle per se. With this implication in mind, I analyze how the volatility of macro and financial variables differs between a steady state with low leverage and one with high leverage, keeping all other parameters at their posterior median value. To implement these two steady states, I adjust the amount of start-up capital brought into the financial system by new bankers. The high leverage steady state regime, with leverage equal to 25, has an economy where a higher fraction of the supply of credit to impatient households and entrepreneurs is dependent on the MBI funding market.

Table B.7 presents the percentage change in the peak impulse response of macro and financial variables in response to shocks across the two leverage regimes. The shocks that are not listed in the table did not have a change in response across regimes.

Among the shocks for which the magnitude of the impulse response changed, there is a clear finding: The volatility of a funding shock is amplified across all variables, whereas he volatility of all other shocks is dampened across all variables with exception to broker-dealer leverage.

To understand these results, recall from Chapter 3.3 that for all non-funding shocks, the supply of credit shifts endogenously (through leverage) in a way that offset shifts in the demand for credit. For example, a shock which decreases the demand for credit lowers the profitability of bankers, decreasing the returns to diverting funds and exiting the financial sector. With less incentive to divert funds and exit the financial sector, funding market conditions improve - leverage rises, increasing the supply of credit. In the steady state with higher leverage, that feature is amplified, making MBIs absorb more of the volatility induced by outside shocks. The reason that leverage adjustments are larger comes from the tradeoff that must be balanced in equilibrium for the funding market to work: the marginal benefit to diverting (defaulting) vs. the marginal benefit from staying in the financial sector. With higher long run leverage, bank net worth is more sensitive to leverage fluctuations - see equation 3.14. By extension, the marginal benefit from staying in the financial sector is also more sensitive to leverage fluctuations. Since leverage is the market mechanism through which the tradeoff between diverting and participating is balanced, larger swings in this tradeoff imply larger swings in leverage and the supply of credit. In the case of outside shocks, larger swings in leverage work to cushion the shocks and lower macro volatility. But in the case of a funding shock, which through collateral and debt deflation effects induces a shift in credit demand which further tightens credit in the economy, larger swings in credit supply produce higher macroeconomic volatility.

The upper panel of Figure D.2.3 presents the median variance decomposition for both steady states. In the higher leverage environment the financial funding shock rises in importance for driving business cycles - it accounts for three times more of the forecast error variance in house prices and investment as it does in the low leverage environment. Monetary policy shocks become particularly less relevant in driving fluctuations - their importance in driving investment, consumption, and house prices is cut in half. Housing demand and entrepreneur credit shocks also become less relevant in driving business cycles.

4.2.2 Effects of higher long-run LTV limits

Another feature marking the evolution of mortgage finance in the last 25 years is the rising average household mortgage LTV ratio. For first-time homebuyers, Duca et al. (2011) document average LTVs of $80 - 85\%$ in the 1980s which rose to the $90 - 95\%$ range from 2000-2005. While there exists some variation in LTV ratios at business cycle frequencies, the dominant feature is a clear upward trend over most of the sample period. Thus, similar to the gradual increase in security broker-dealer leverage over the sample, changes in the mortgage market are likely better captured as a long-run shift in the mortgage market as opposed to a transitory shock. To capture the effects of this structural change on the propagation of shocks in the business cycle, I compare the change in volatility of macro and financial variables when moving from a "low LTV" steady state ($m_i = 0.8$) to a "high LTV" steady state ($m_i = 0.95$).

Table B.8 presents the percentage change in the peak impulse response of macro and financial variables in response to shocks across the two LTV regimes. The shocks that are not listed in the table did not have a change in response across regimes. Apart from the propagation of business loans, the higher LTV steady state features higher volatility across all shocks and variables. Iacoviello (2005) and Walentin (2011) find a similar result with respect to consumption, but do not look at house prices, credit, or broker-dealer leverage.

The increased volatility comes from stronger debt deflation and collateral effects. In the higher LTV steady state, the real debt burden of impatient households is higher, making their disposable income more sensitive to debt deflation and fluctuations in borrowing constraints brought about by collateral effects. As a result, any shock causes disposable income for impatient households to fluctuate more widely, leading to larger fluctuations in consumption, credit, house prices, and leverage.

The lower panel of Figure D.2.3 presents the median variance decomposition for both steady states. Housing demand shocks are particularly amplified with higher LTV limits, accounting for ten-times more of the forecast error variance in consumption as in the low LTV steady state, and twice as much of the forecast error variance in investment and broker-dealer leverage. The financial funding shock also becomes more important in driving business cycles, particularly with respect to house prices and consumption.

4.2.3 Summary

Although the exercise is suggestive, the implications of the model in an environment of higher long-run leverage for MBIs and LTV limits for households makes both sectors important in understanding business cycles. If the early 1980s are considered to be an environment with "low LTV, low leverage," while the 2000s are a "high LTV, high leverage" environment, then this exercise offers an additional reason why housing and MBIs matter so much more in explaining the Great Recession relative to earlier in the sample. Higher LTV limits for households and leverage for MBIs makes the economy unambiguously more vulnerable to financial funding shocks, and potentially more vulnerable to housing demand shocks.

Looking beyond the Great Recession, the major implication of this exercise - that MBIs reduce volatility from outside shocks but only at a cost of increasing their own importance in creating volatility - lends support to two very different (but not mutually exclusive) views about finance in the business cycle. On the one hand, the model is consistent with the idea that the financial innovation of the 1980s and 1990s, which created the environment for MBIs, contributed to the Great Moderation.[6] On the other hand, the model is also consistent with the argument that too much reliance on market-based intermediation can put the economy at risk of shocks originating from within the financial sector, an idea the goes all the way back to at least Minksy (1982) but was articulated at the 2005 Federal Reserve Jackson Hole Symposium just before the housing bust by Rajan (2005).

[6]See Bernanke (2004) for an overview of the main hypothesis for the Great Moderation. For arguments that financial innovation played a role in the Great Moderation, see, for example, Dynan et al. (2006) and Greenspan (1999). For evidence that finance was not important in the Great Moderation (which doesn't simply cite the financial crisis and Great Recession as proof), see den Haan (2010).

CHAPTER 5

CONCLUSION

The disparity of the evidence for the "smoking gun" which caused the Great Recession is not so much a failure of the economics profession to come to a consensus as it is evidence that the Great Recession has no "smoking gun" cause. The structural evidence from this paper supports a growing consensus that the Great Recession was an unprecedented confluence of large shocks, only some of which were directly related to the housing market and financial sector.

By and large, the housing market and intricacies of the financial sector were ignored in mainstream business cycle analysis before the Great Recession.[1] After disentangling the role of housing demand shocks and shocks which affect funding conditions for security broker-dealers, the assumed immateriality of the shocks prior to the Great Recession seems less suspect. Traditional macroeconomic shocks can account for the majority of movements in consumption, investment, house prices, credit, and even security broker-dealer leverage. Financial funding shocks are most important in explaining rising MBI leverage and credit over the sample. Positive funding shocks also supported higher consumption in the 2000s, were the principal cause of the early stages of the most recent housing boom, and accounted for investment dynamics around the 2000 and especially 2008 recession. Of less importance, housing demand shocks played a nontrivial role in the dynamics in investment, credit, and house prices only late in the most recent housing boom.

The impact of higher household and MBI leverage over the sample, in the wake of financial innovation/deregulation during the 1980s/1990s, is at least as important as the shocks originating from housing and MBIs. Deregulation, which allowed the environ-

[1] See Smets and Wouters (2007), Justiniano et al. (2011), and Christiano et al. (2009) for standard business cycle models.

ment for MBIs to increase in size and scope in determining the supply of credit, increases the ability of the financial system to cushion the economy from macro shocks. However, the economy is made more vulnerable to shocks originating within the financial sector. Higher household indebtedness, despite increasing initial consumption, also makes the economy more sensitive to shocks. In terms of the Great Recession, the analysis confirms that not only was it a recession associated with uncharacteristically large financial and housing market shocks, but the environment surrounding the shocks made the economy more responsive to them.

APPENDIX A

DATA SOURCES

- Aggregate consumption: Real Personal Consumption Expenditure (seasonally adjusted, deflated with the implicit price deflator for the nonfarm business sector), divided by the Civilian Noninstitutional Population (CNP16OV, source: BLS). Source: BEA.
- Business Fixed Investment: Real Private Nonresidential Fixed Investment (seasonally adjusted, deflated with the implicit price deflator for the nonfarm business sector, divided by the CNP16OV. Source: BEA.
- Real House Prices: Census Bureau House Price Index (new one-family houses sold including value of lot) deflated with the implicit price deflator for the nonfarm business sector. Source: Census Bureau.
- Hours in the non-construction sector: Total Nonfarm Payrolls (Series ID: PAYEMS in the St. Louis FRED database) less all employees in the construction sector (Series ID: USCONS), times Average Weekly Hours of Production and Nonsupervisory Workers (Series ID: ANHNONAG), divided by the CNP16OV. Source: BLS.
- Real Wages: Average Hourly Earnings of Production and Nonsupervisory Workers (Series ID: CES2000000008), deflated by the implicit price deflator for the nonfarm business sector. Source: BLS.
- Residential Mortgages: Home Mortgages (Table L.100, Federal Reserve Flow of Funds), deflated by the implicit price deflator for the nonfarm business sector, divided by the CNP16OV. Source: U.S. Federal Reserve Flow of Funds.
- Business debt: Credit market instruments of all nonfarm, nonfinancial corporate (Table L.102) and noncorporate (Table L.103), deflated by the implicit price deflator for the nonfarm business sector, divided by the CNP16OV. Source: U.S. Federal Reserve Flow of Funds.
- Leverage: Total Financial Assets divided by Total Equity (Total Financial Assets minus Total Liabilities) of Security Broker Dealers. Source: U.S. Federal Reserve Flow of Funds.
- Inflation: Quarter on quarter log differences in the implicit price deflator for the nonfarm business sector, demeaned. Source: St. Louis FRED.
- Nominal Short-term Interest Rate: 3-month Treasury Bill Rate (Secondary Market Rate), expressed in quarterly units, demeaned. Source: St. Louis FRED.

APPENDIX B
TABLES

Table B.1: Calibrated Parameters

Discount factors	$\beta_p, \beta_i, \beta_e$	$0.9925, 0.97, 0.96$
Housing utility parameters	j_p, j_i	$0.22, 1.87$
Impatient household LTV	m_i	0.80
Share of capital in production	α	0.325
Share of housing in production	ν	0.035
Entrepreneur LTV	m_e	0.55
Capital depreciation rate	δ	0.03
Steady state markup	X	1.15
Autocorrelation of inflation objective shock	ρ_s	0.975
Leverage ratio of financial sector	ϕ	21

Table B.2: Empirical Targets for Calibrated Parameters

Real interest rate	$4r-1$	3%
Mortgage-Treasury spread	$4(r_b - r)$	1.7%
Investment share	$\frac{I}{Y}$	17%
Household real estate wealth	$\frac{qh_i+qh_p}{Y}$	1.7
Business sector real estate wealth	$\frac{qh_e}{Y}$	1.3
Mortgage debt-to-output	$\frac{b_i}{Y}$	0.64
Broker-dealer leverage	ϕ	21

Table B.3: Estimated Parameters

	Prior	Prior mean	Prior s.d.	Post. mean	Post. s.d.	10%	90%
χ_i	Γ	0.5	0.05	0.60	0.057	0.52	0.68
χ_p	Γ	0.5	0.05	0.48	0.047	0.42	0.54
σ	β	0.65	0.05	0.69	0.041	0.63	0.74
Ω	Γ	2.1	0.275	1.06	0.135	0.89	1.25
ϕ_p^h	Γ	2.1	0.275	0.06	0.008	0.045	0.066
$100\gamma_k$	N	−0.24	0.01	−0.25	0.009	−0.259	−0.2378
$100\gamma_c$	N	0.45	0.01	0.44	0.008	0.428	0.451
$100\gamma_h$	N	0.38	0.01	0.41	0.01	0.392	0.418
ϵ_i	β	0.8	0.075	0.77	0.026	0.74	0.81
ϵ_p	β	0.8	0.075	0.48	0.055	0.41	0.55
ϵ_e	β	0.5	0.075	0.41	0.071	0.32	0.49
ρ_y	N	0	0.1	0.27	0.058	0.19	0.35
ρ_r	β	0.75	0.1	0.72	0.033	0.68	0.76
ρ_π	N	1.5	0.1	1.82	0.082	1.71	1.93
ζ	β	0.65	0.03	0.86	0.01	0.85	0.88
$\iota,$	β	0.50	0.2	0.96	0.021	0.92	0.98
ρ_j	β	0.8	0.1	0.9934	0.0378	0.987	0.998
ρ_λ	β	0.8	0.1	0.9197	0.0138	0.90	0.94
ρ_e	β	0.8	0.1	0.9867	0.0071	0.97	0.99
ρ_τ	β	0.8	0.1	0.1627	0.0378	0.11	0.22
ρ_z	β	0.8	0.1	0.9007	0.019	0.87	0.93
ρ_c	β	0.8	0.1	0.9938	0.0025	0.988	0.998
ρ_k	β	0.8	0.1	0.9821	0.0190	0.97	0.99
$10u_\lambda$	inv-Γ	0.1	1	0.9030	0.0979	0.78	1.04
$10u_\tau$	inv-Γ	0.1	1	1.3962	0.1006	1.27	1.53
$10u_e$	inv-Γ	0.1	1	0.0773	0.0089	0.06	0.89
$10u_c$	inv-Γ	0.1	1	0.0884	0.0117	0.07	0.11
$10u_k$	inv-Γ	0.1	1	0.1369	0.0142	0.12	0.16
$10u_z$	inv-Γ	0.1	1	0.2925	0.0382	0.24	0.35
$10u_j$	inv-Γ	0.1	1	0.4877	0.0569	0.38	0.63
$10u_r$	inv-Γ	0.1	1	0.0158	0.0014	0.014	0.018
$100u_\pi$	inv-Γ	0.1	1	0.2913	0.0369	0.24	0.35
$1000u_s$	inv-Γ	0.1	1	0.4886	0.1065	0.35	0.64
$ME(w)$	inv-Γ	0.1	1	0.1354	0.0098	0.12	0.15

Table B.4: Business Cycle Properties of the Model (HP-Filter, $\lambda = 1600$)

Correlations	2.5%	5%	Median	Data	95%	97.5%
Output, Consumption	0.64	0.68	0.87	0.94	0.94	0.95
Output, Investment	0.82	0.84	0.93	0.91	0.97	0.98
Output, House price	0.47	0.51	0.71	0.42	0.83	0.84
Output, Total credit	0.64	0.68	0.83	0.64	0.91	0.92
Output, Leverage	−0.56	−0.53	−0.25	0.02	0.10	0.30
House price, Leverage	−0.33	−0.29	−0.01	−0.21	0.28	0.30
House price, Mortgage credit	0.56	0.59	0.76	0.70	0.87	0.88
House price, Consumption	0.14	0.20	0.57	0.46	0.79	0.80
House price, Inflation	−0.14	−0.09	0.22	0.38	0.48	0.50
Mortgage credit, Consumption	0.10	0.16	0.55	0.39	0.78	0.79
Mortgage credit, Leverage	−0.67	−0.64	−0.44	−0.22	−0.16	−0.14

Table B.5: Importance of rigidities

No habit	No index	$\zeta = .1$	No adj.	Full sticky	Full adj.	Base
Marginal likelihood						
2075	2060	1232	1993	2145	2005	2164

Table B.6: Variance Decomposition: Average median 1,4,8 quarter value

	Labor pref.	Discount factor	Cost push	Monetary	Infl. tgt.	TFP	IST	Ent. credit	Total Macro	Funding	Housing pref.	Total Non-Macro
Output	1.37	2.07	38.43	5.23	20.77	11.87	2.80	3.93	86.47	8.77	2.67	11.43
Inv.	1.10	3.30	36.80	5.07	20.67	3.90	2.82	6.47	80.12	14.40	3.33	17.73
Cons.	2.17	15.13	29.40	4.27	15.67	21.93	3.83	1.13	93.53	2.40	1.53	3.93
Infl.	27.47	6.60	14.50	4.17	36.10	0.08	0.56	1.77	91.24	5.03	2.43	7.47
Int. rate	27.53	9.70	3.47	3.43	31.97	1.10	1.83	4.07	83.10	10.77	4.67	15.43
House price	1.90	8.60	18.77	3.90	12.47	6.80	1.67	1.10	56.30	6.57	35.23	41.80
Mortgages	21.30	0.90	21.77	4.30	15.10	2.37	0.53	0.80	67.07	10.37	20.77	31.13
Bus. loan	1.53	0.49	21.33	4.73	16.00	0.73	13.73	19.07	77.62	18.60	2.43	21.03
Tot. loans	9.10	0.47	24.10	5.23	17.50	1.60	5.63	7.90	71.54	16.27	10.33	26.60
Lev.	24.93	0.57	17.53	5.67	18.03	0.73	5.23	6.30	79.00	9.37	9.63	19.00

Table B.7: Sensitivity of the economy to long-run financial sector leverage

Variable	**Shock, % Change in amplitude of impulse responses, $\phi = 15 \rightarrow 25$**					
	Financial	Entrepreneur credit	Housing pref.	i.i.d. Monetary	Inflation tgt.	Cost-push
Output	11	−47	−62	−41	−39	−33
Consumption	12	−45	−48	−27	−29	−22
Investment	67	−41	−68	−48	−46	−40
House price	59	−51	−21	−35	−38	−38
Mortgages	42	−90	−29	−44	−46	−41
Business loans	27	−38	−94	−59	−60	−57
Leverage	270	149	150	155	161	173
Inflation	50	−51	−51	−33	−24	−41

Table B.8: Sensitivity of the economy to long-run mortgage LTV limit

Variable	**Shock, % Change in amplitude of impulse responses,** $m_i = .80 \rightarrow .95$					
	Financial	Entrepreneur credit	Housing pref.	i.i.d. Monetary	Inflation tgt.	Cost-push
Output	36	31	68	44	38	25
Consumption	73	64	83	64	62	51
Investment	8	10	31	17	13	5
House price	42	25	40	39	40	34
Mortgages	77	81	79	80	80	77
Business loans	−104	−15	58	−82	−69	−70
Leverage	75	66	85	79	80	80
Inflation	65	64	83	65	49	42

APPENDIX C
FIGURES

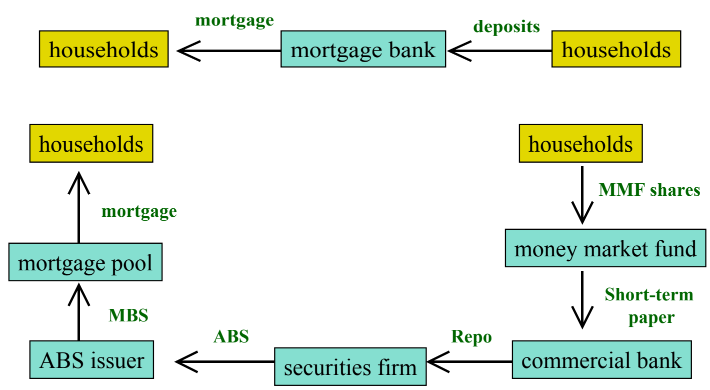


Figure C.1: Bank vs. Market-based Intermediation

Figure credit: Adrian and Shin (2010c)

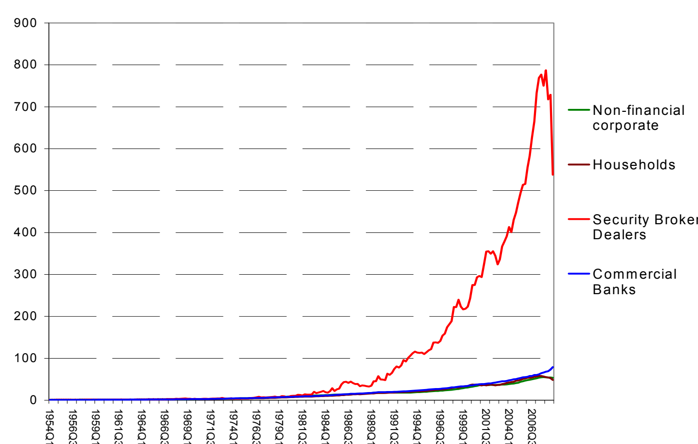
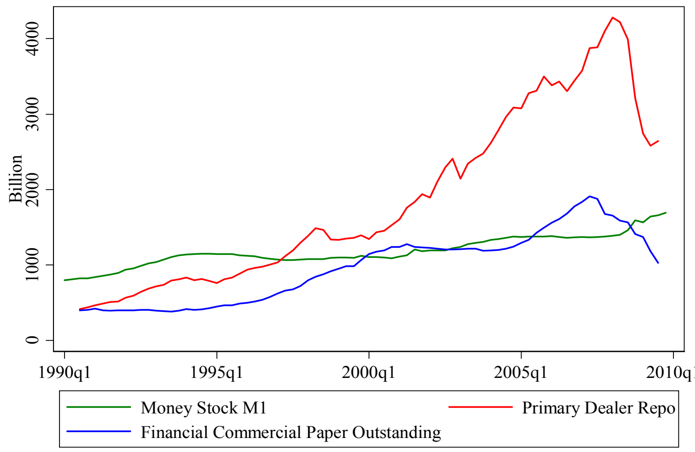


Figure C.2: Assets across business and financial entities

Figure credit: Adrian and Shin (2010c)



Sources: Board of Governors of the Federal Reserve and Federal Reserve Bank of New York

Figure C.3: The size of broker-dealer funding markets

Figure credit: Adrian and Shin (2010c)

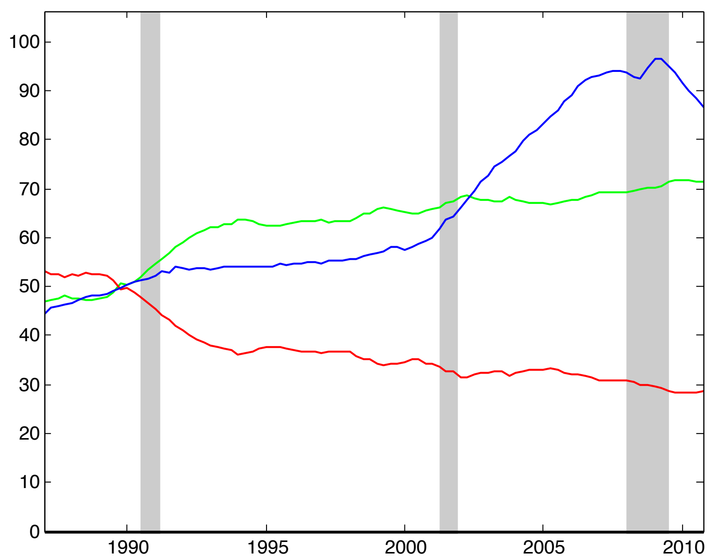


Figure C.4: The composition of mortgage finance

Green line: Mortgage debt outstanding as a percentage of GDP.
Red line: Percentage of mortgages outstanding held by commercial banks, savings and loans, and credit unions.
Blue line: Percentage of mortgages outstanding held by GSEs, Finance Companies, ABS Issuers, and Real Estate Investment Trusts.

All data taken from the Flow of Funds.

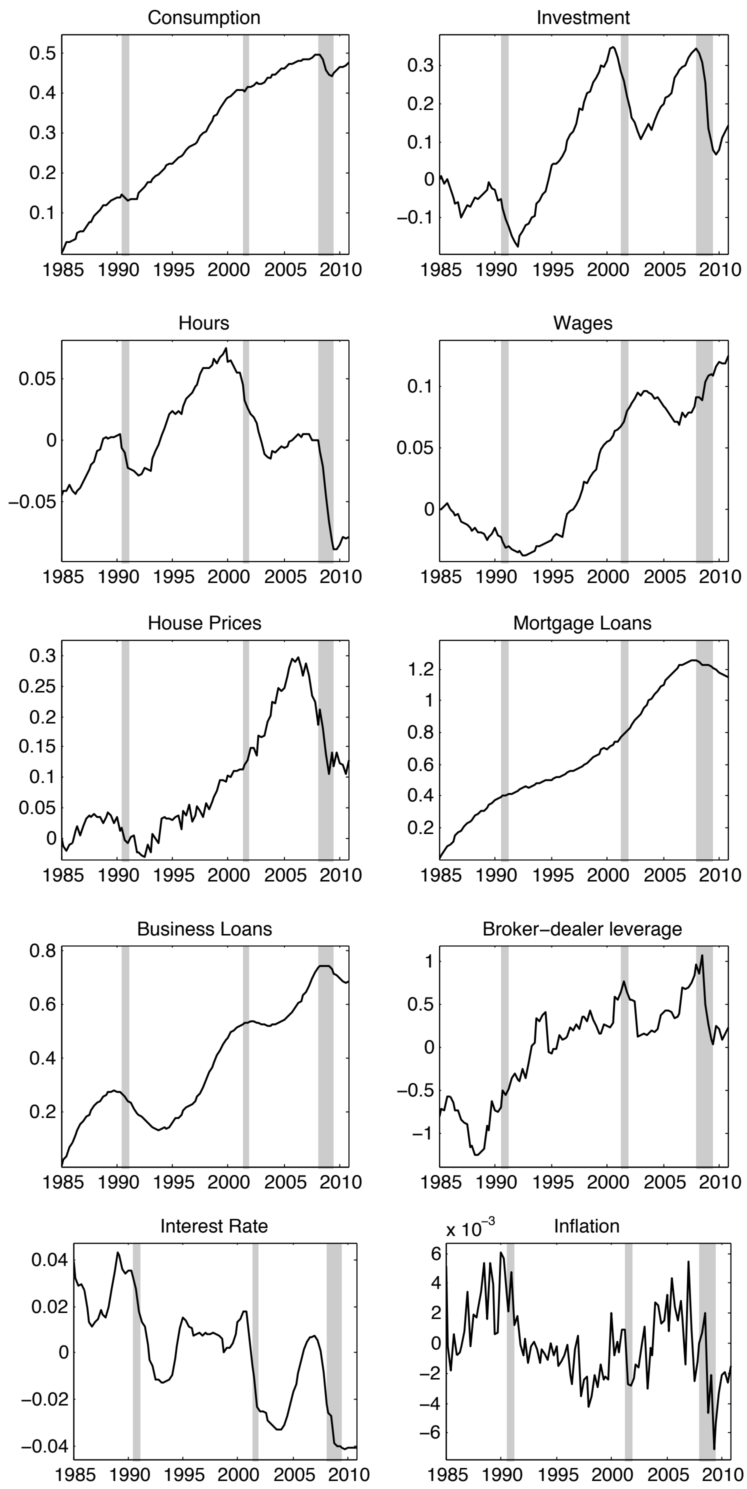


Figure C.5: The data

All data are log-transformed. Consumption, investment, lending and house prices are all normalized to zero in 1985.1. Hours, the nominal interest rate and leverage are demeaned.

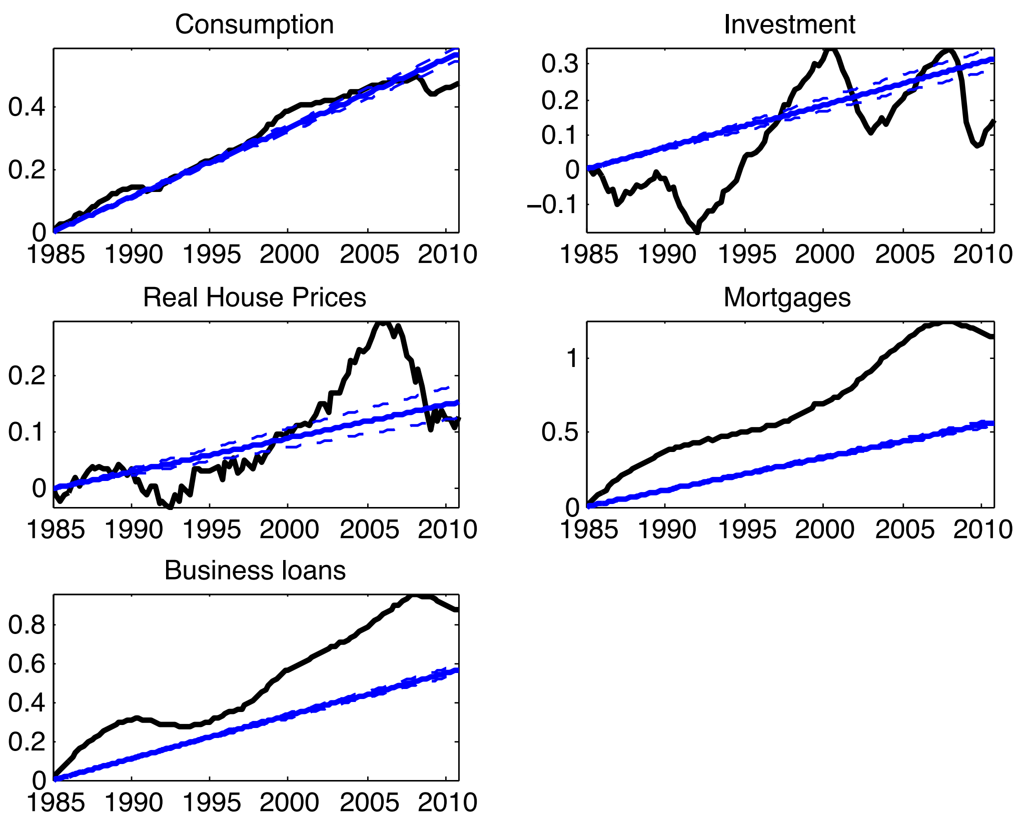


Figure C.6: Data with estimated trends

Blue line: Median estimated trend
Dashed lines: 95% probability intervals.

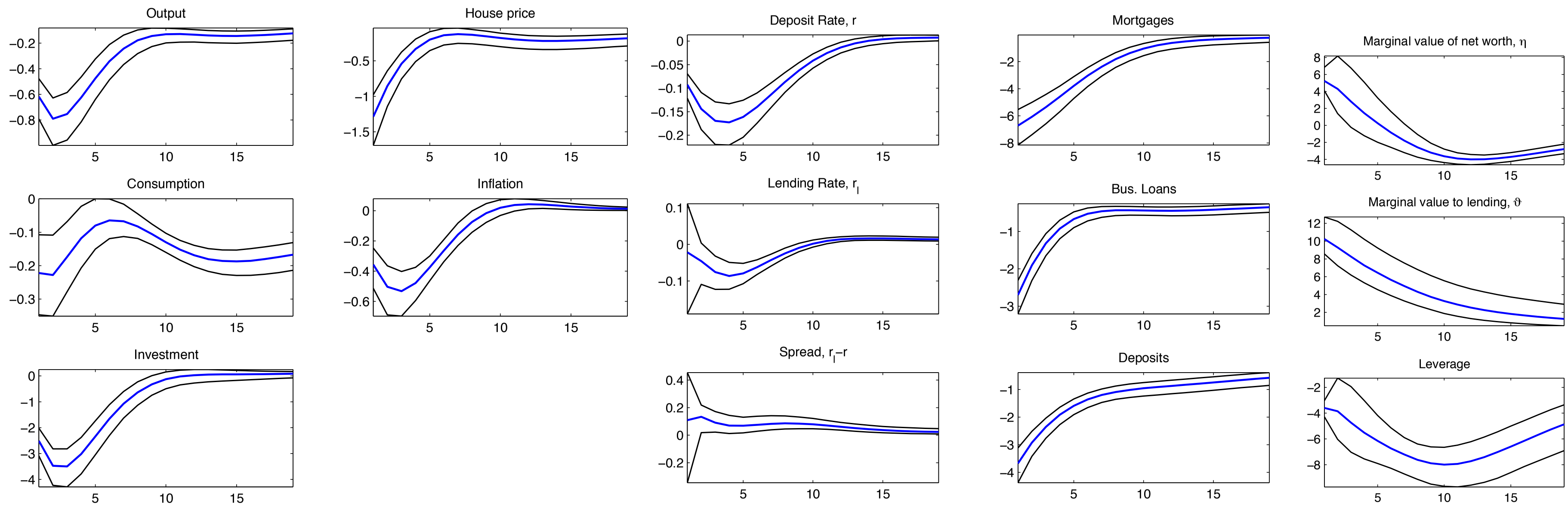


Figure C.7: Impulse response to a negative one standard deviation financial funding shock

Blue line: median response.
Black lines: 95% probability intervals.
Coordinate: Percentage deviation from steady state, interest rates and inflation expressed as annualized change

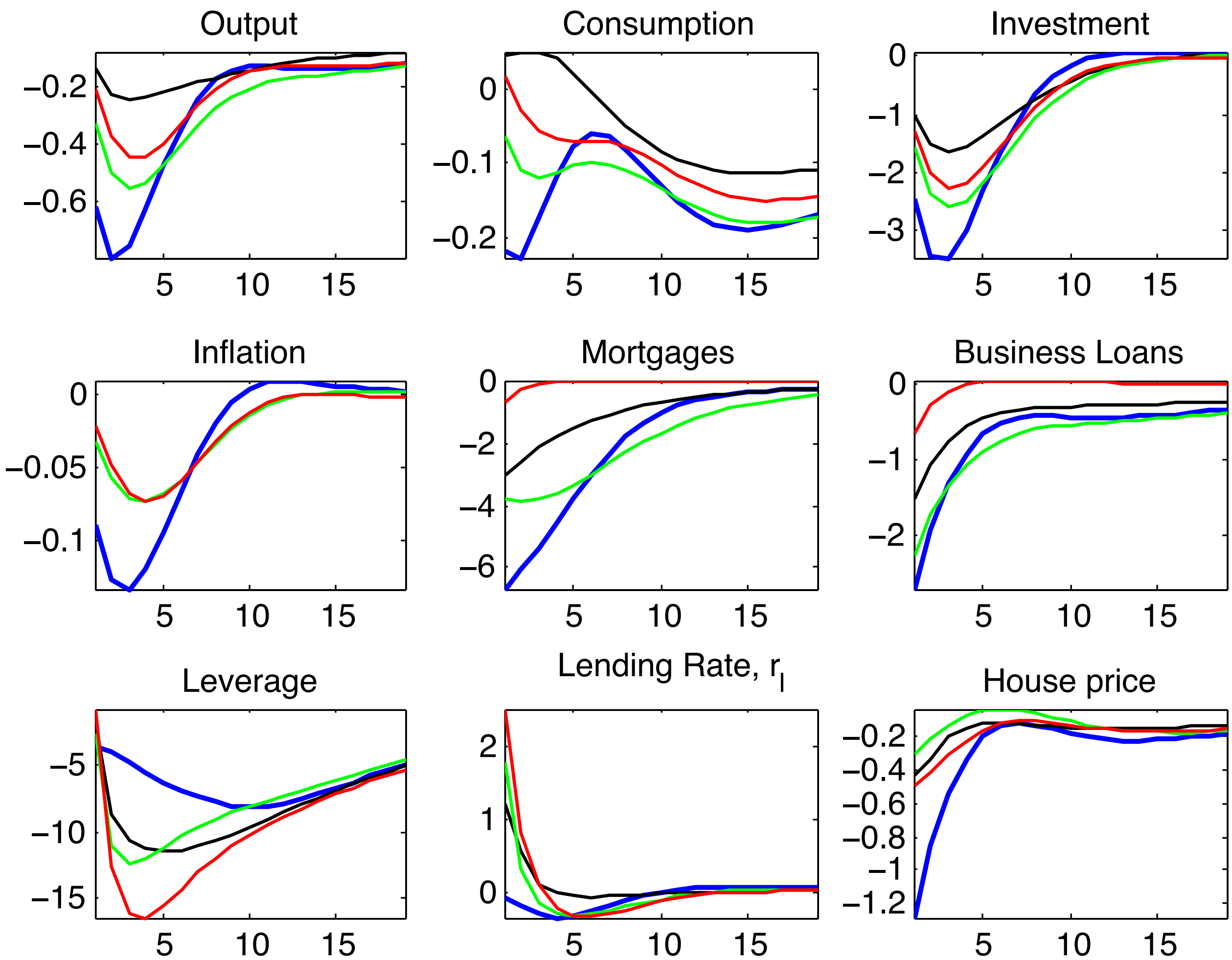


Figure C.8: Decomposing the financial funding shock

Blue: baseline model
Black: flexible prices
Green: no housing adjustment cost
Red: no collateral effects

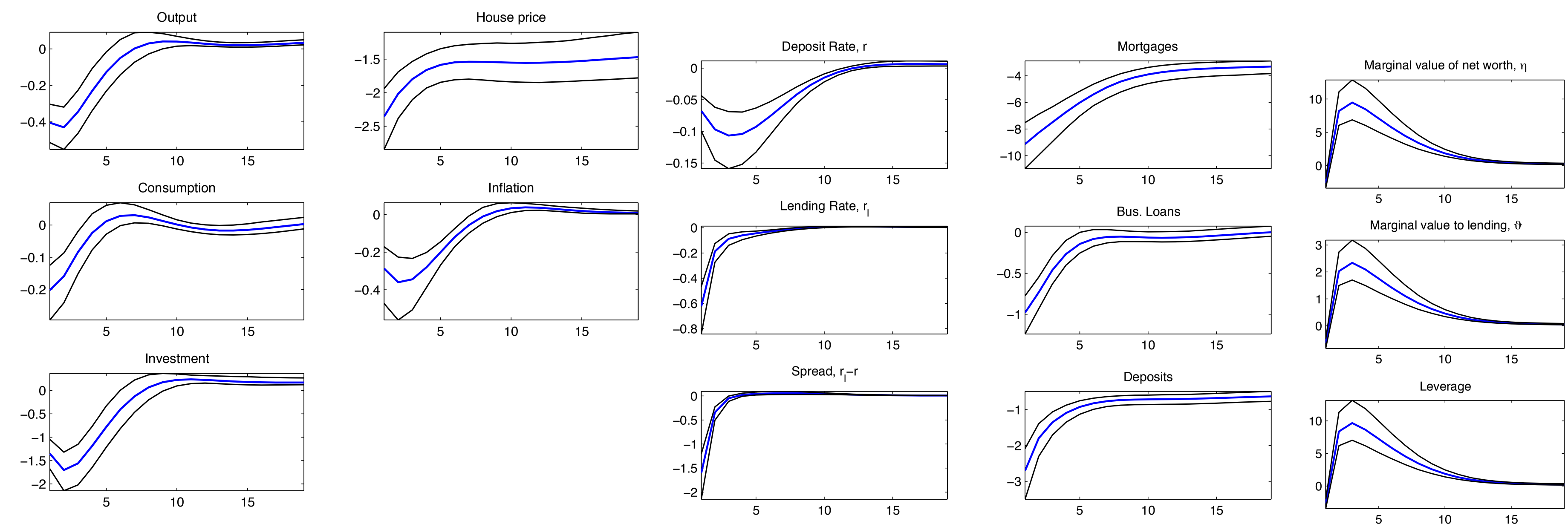


Figure C.9: Impulse response to a negative one standard deviation housing demand shock

Blue line: median response.
Black lines: 95% probability intervals.
Coordinate: Percentage deviation from steady state, interest rates and inflation expressed as annualized change

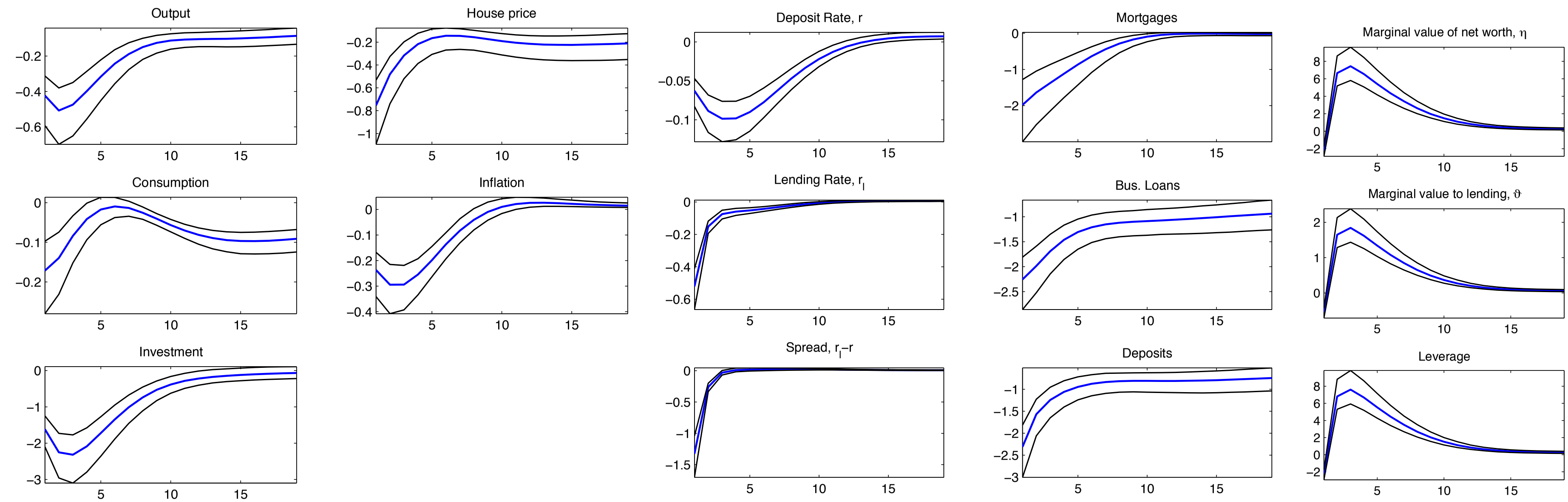


Figure C.10: Impulse response to a negative one standard deviation entrepreneur credit shock

Blue line: median response.
Black lines: 95% probability intervals.
Coordinate: Percentage deviation from steady state, interest rates and inflation expressed as annualized change

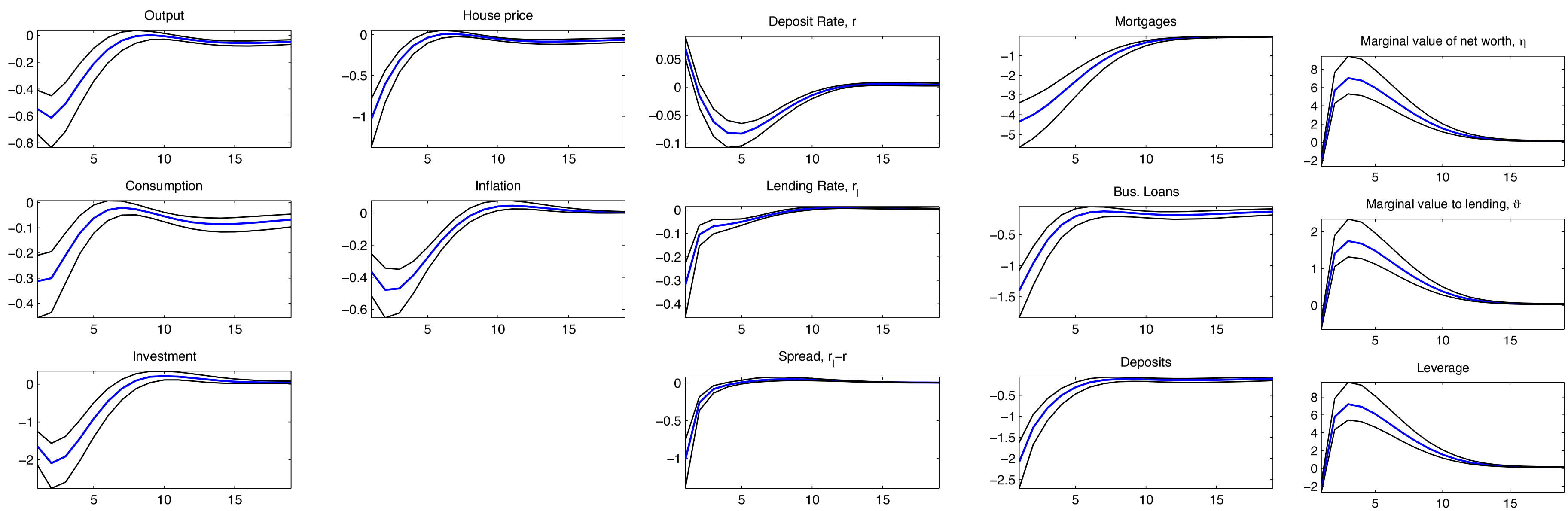


Figure C.11: Impulse response to a negative one standard deviation monetary policy shock

Blue line: median response.
Black lines: 95% probability intervals.
Coordinate: Percentage deviation from steady state, interest rates and inflation expressed as annualized change

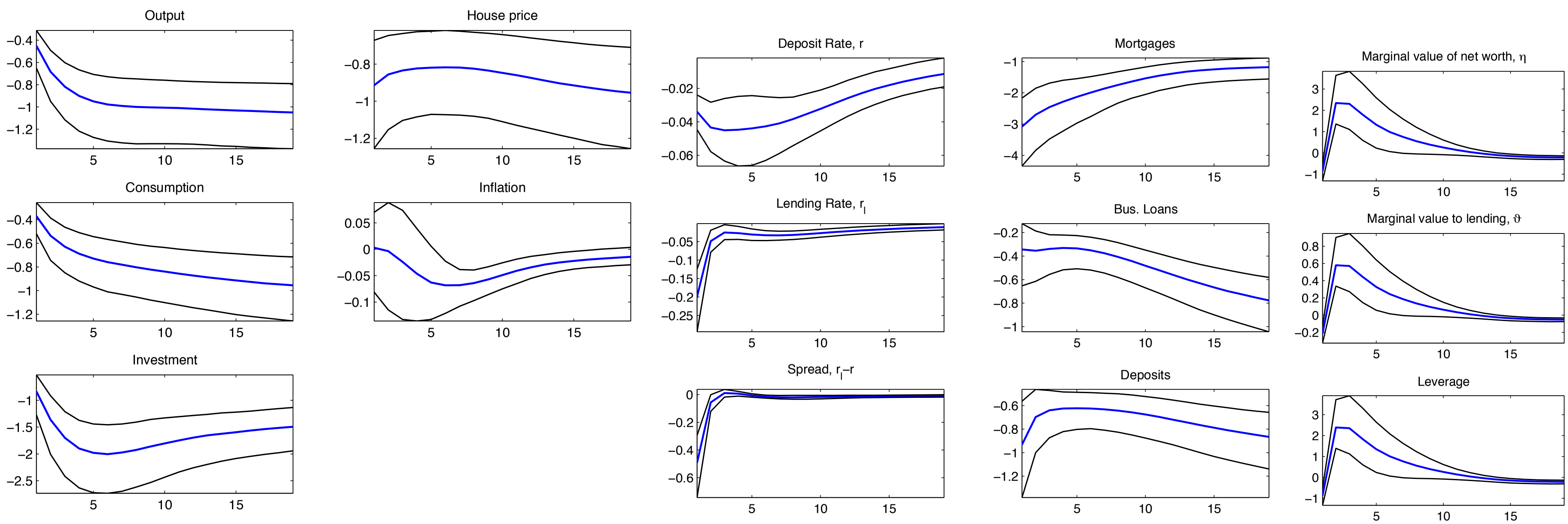


Figure C.12: Quarterly impulse response to a negative one standard deviation TFP shock

Blue line: median response.
Black lines: 95% probability intervals.
Coordinate: Percentage deviation from steady state, interest rates and inflation expressed as annualized change

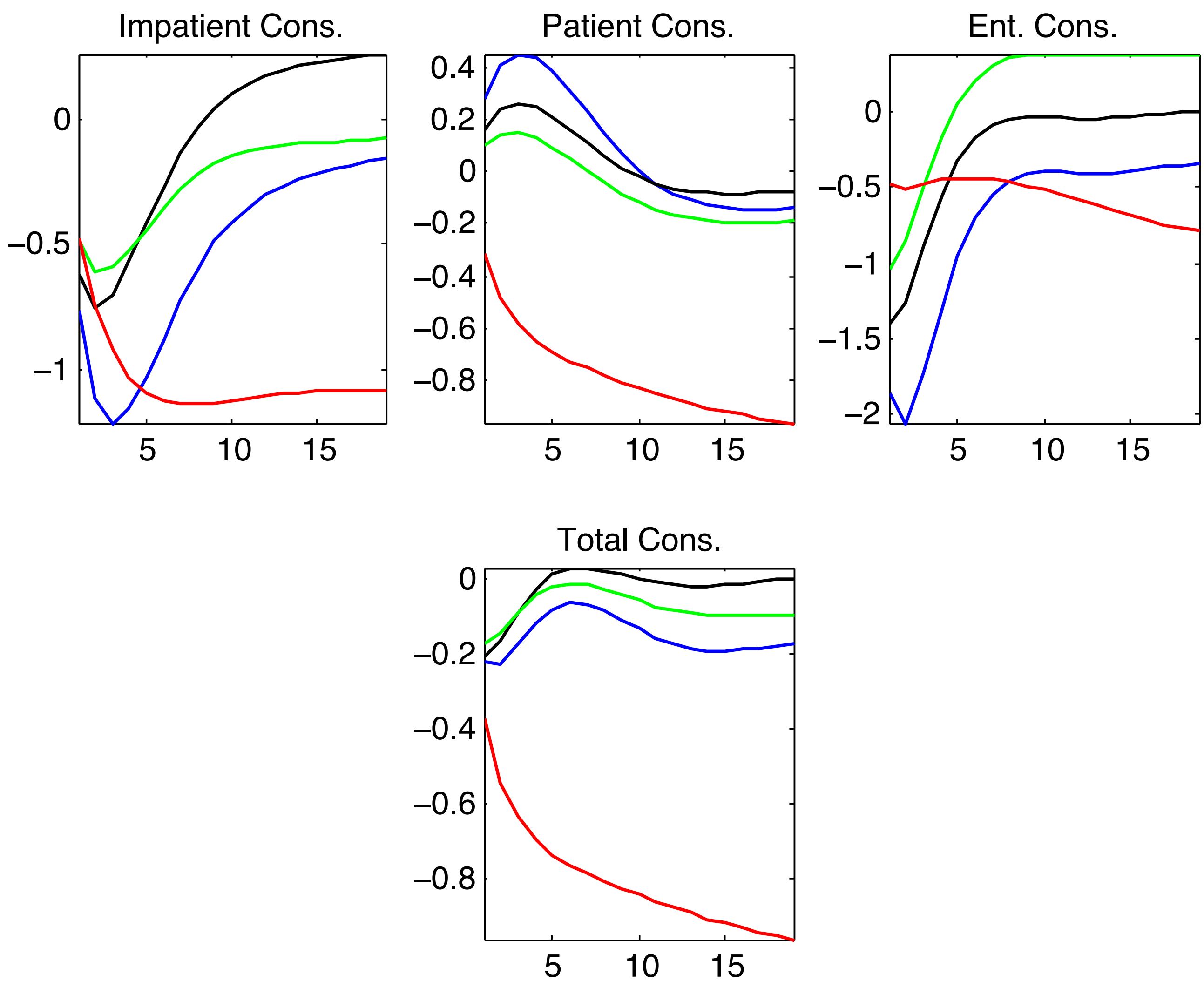


Figure C.13: Explaining the weak consumption response across financial, housing, credit shocks

Blue line: financial funding shock
Black line: housing demand shock
Green line: entrepreneur credit shock
Red line: TFP shock

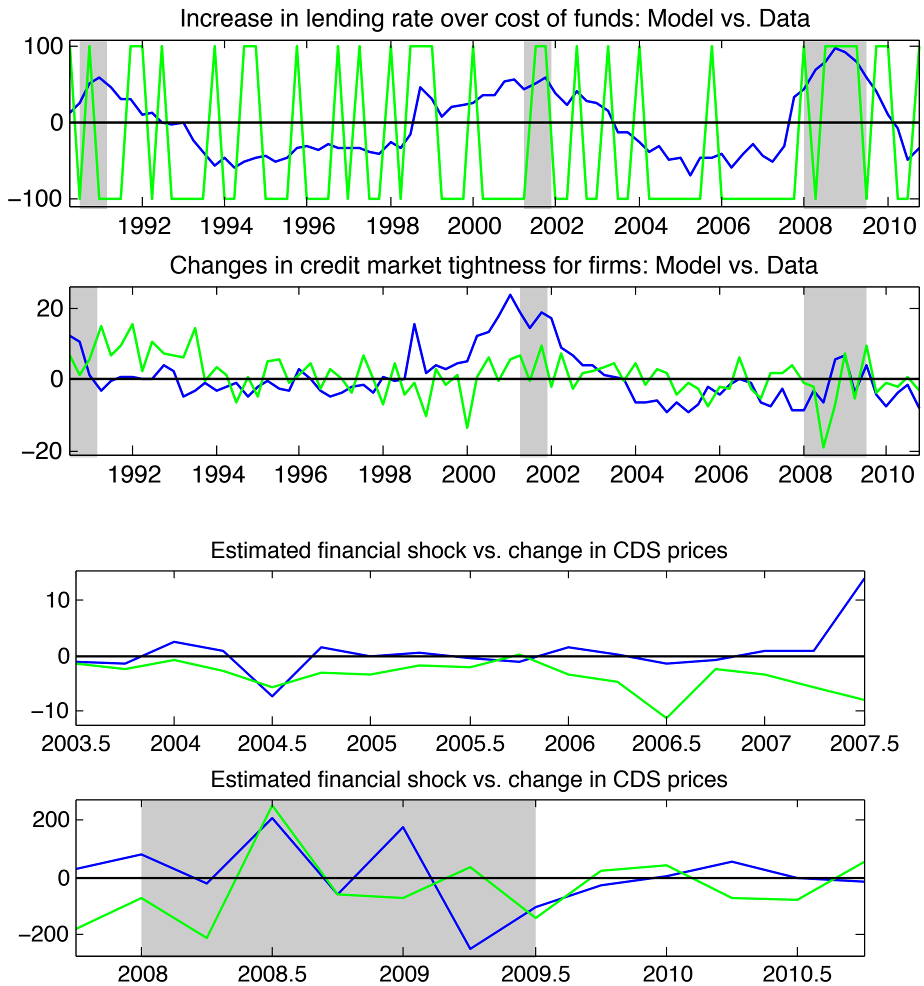


Figure C.14: Comparison of ex-post model data with Federal Reserve Senior Loan Officer Survey Data

First panel:
<u>Green line</u>: qualitative indicator of ex-post lending-deposit spread. 100 = spread above steady state, -100 = spread below steady state.
<u>Blue line</u>: Net percentage of bankers increasing lending rates to firms over their own cost of funds, Senior Loan Officer Survey, Federal Reserve Board.
Second panel:
<u>Green line</u>: Negative of the estimated entrepreneur credit shock.
<u>Blue line</u>: Percentage of bankers tightening lending standards for loans to firms, net the percentage of bankers tightening lending standards for mortgages, Senior Loan Officer Survey, Federal Reserve Board.
Third and Fourth panel:
<u>Green line</u>: Estimated financial funding shock.
<u>Blue line</u>: Change in credit default swap prices for the primary dealers.

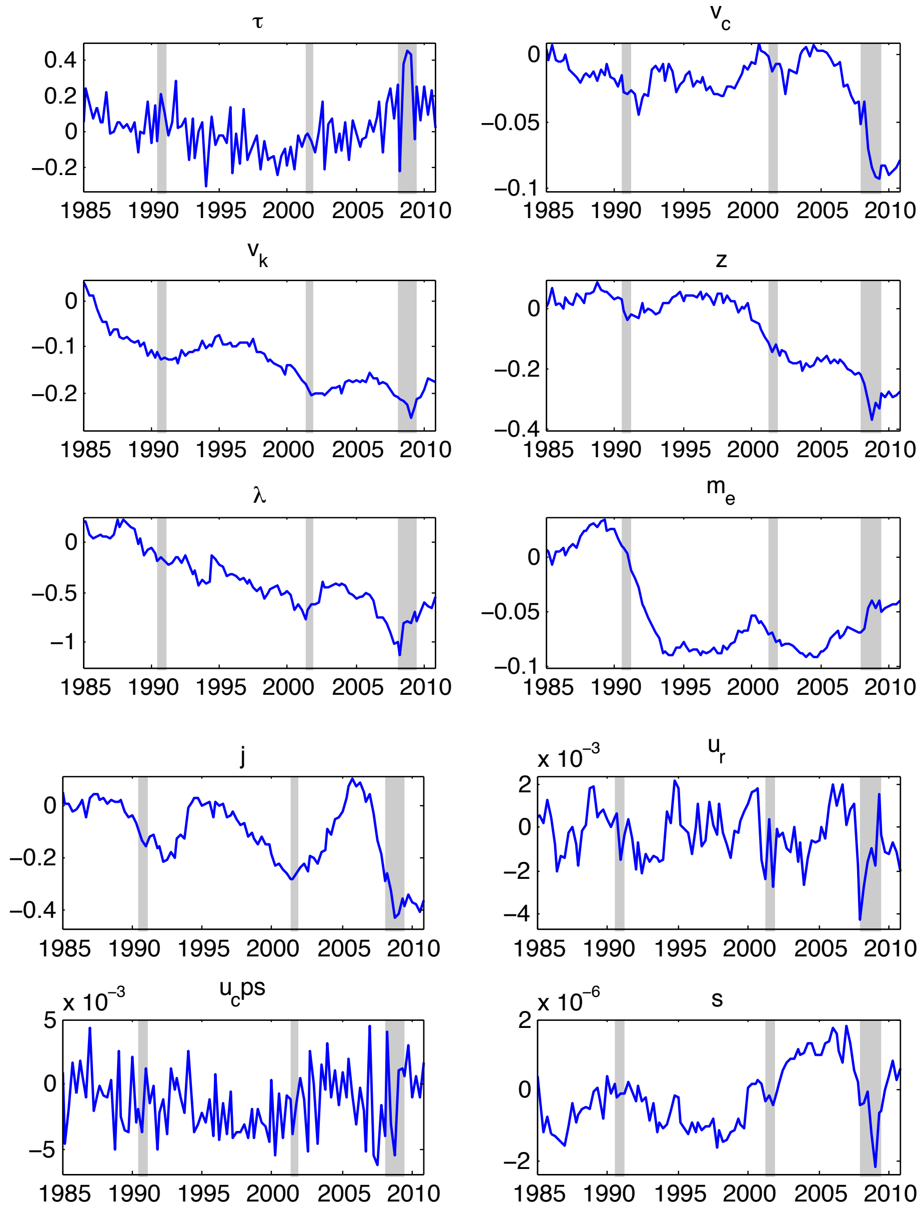


Figure C.15: Estimated exogenous processes.

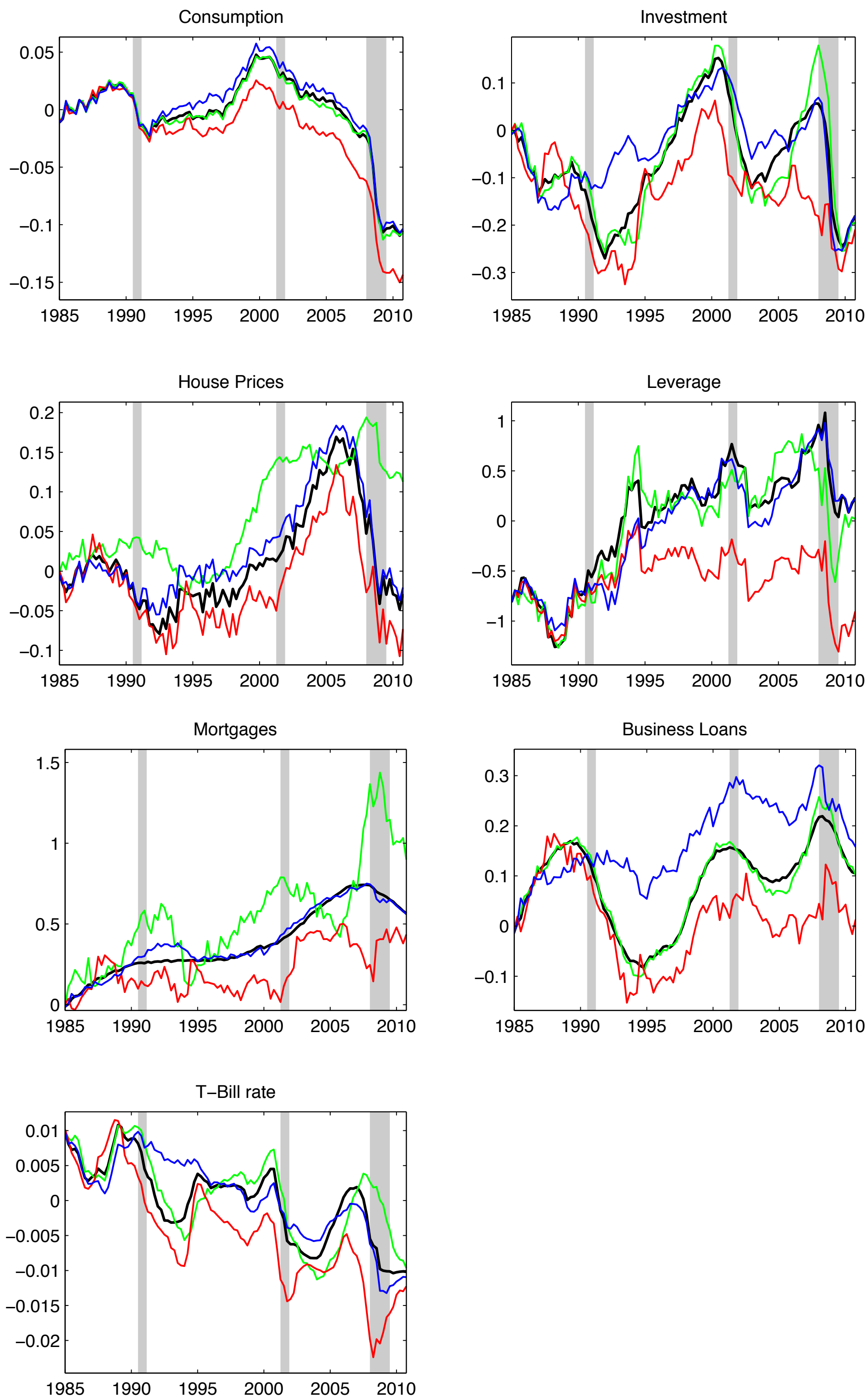


Figure C.16: Historical decomposition of the smoothed shocks, 1

Black: data
Green: **without** housing demand shocks
Blue: **without** Ent. credit shocks
Red: **without** Financial sector funding shocks

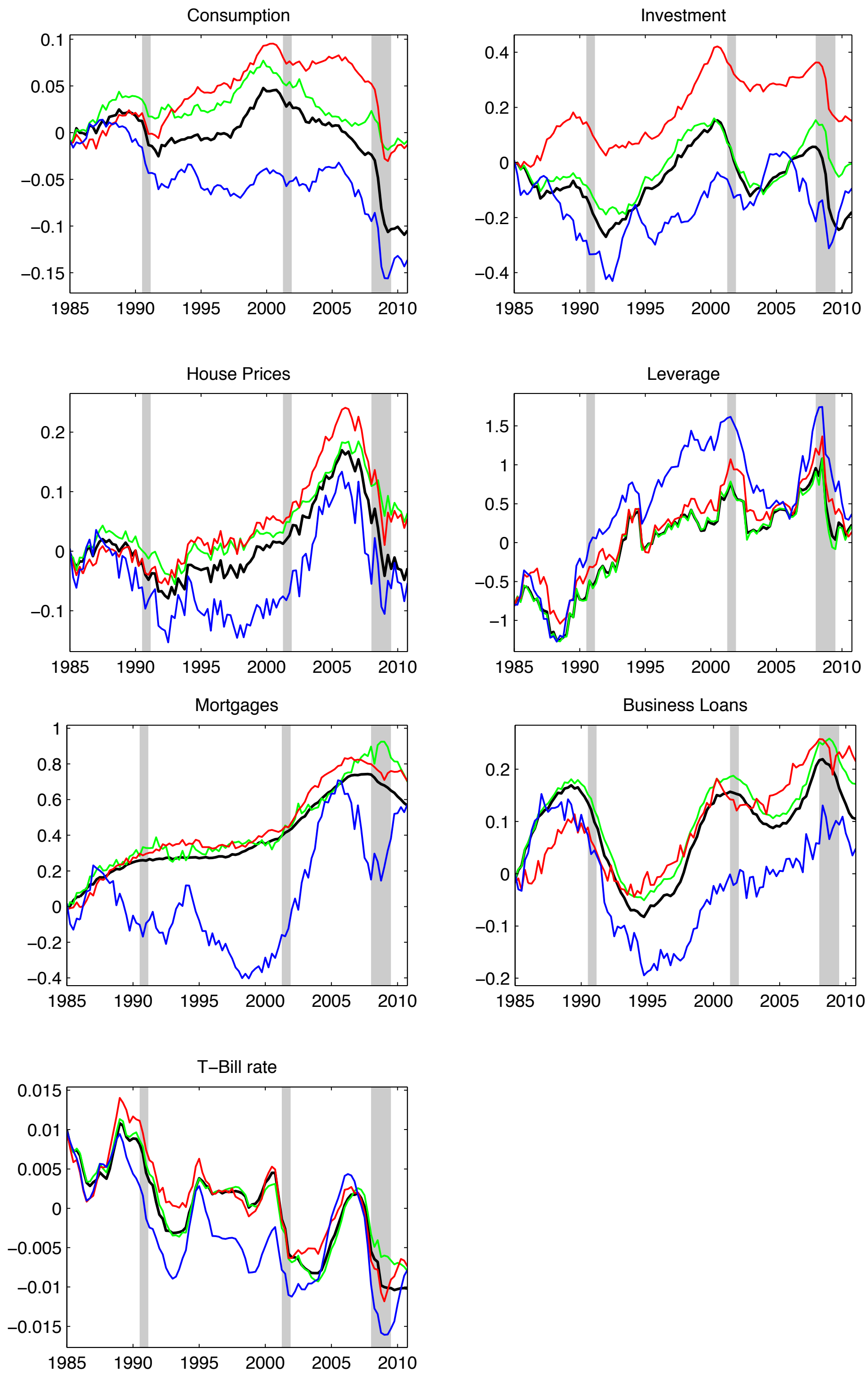


Figure C.17: Historical decomposition of the smoothed shocks, 2

Black line: data
Green: **without** TFP shocks
Blue: **without** Cost-push shocks
Red: **without** IST shocks

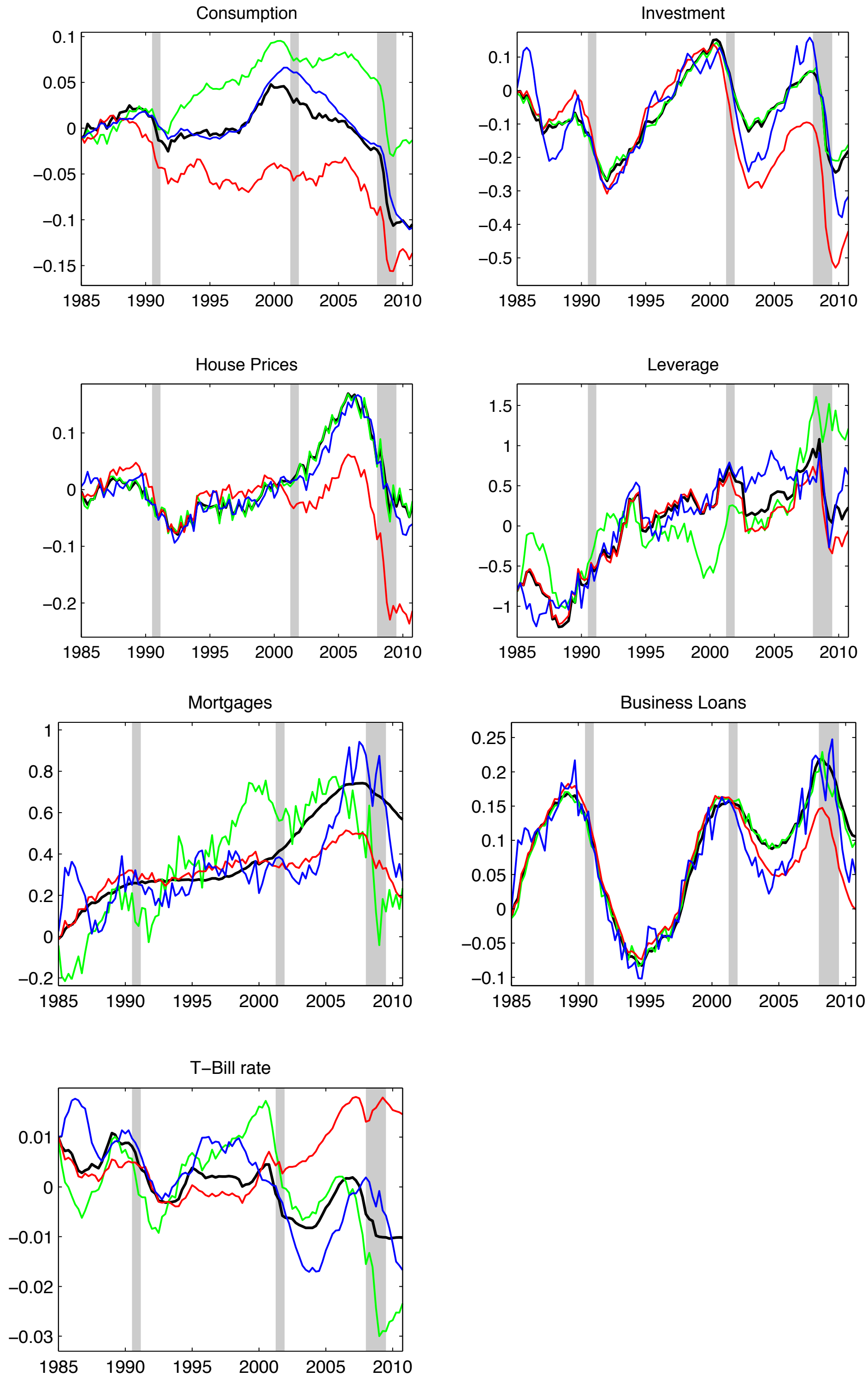


Figure C.18: Historical decomposition of the smoothed shocks, 3

Black: data
Green: **without** Labor preference shocks
Blue: **without** Monetary shocks (i.i.d. + inflation targeting)
Red: **without** Discount factor shocks

APPENDIX D
TECHNICAL APPENDIX

D.1 Model equations, derivations, and balanced growth

D.1.1 Derivation of borrowing constraints

The borrowing constrained faced by entrepreneurs and households can be derived as an optimal contract between borrowers and lenders given the following four assumptions:

1. Borrowers cannot commit to repay their debt.
2. The decision to default on a loan taken out in period t is made at the beginning of period $t+1$, before the realization of aggregate shocks.
3. In the event of default, ownership of the assets which were financed by the loan are transferred to the lender at the end of the period, after the realization of aggregate shocks.
4. Lenders can only recover the fraction $(1 - m_t)q_{t+1}h_t$ of the asset value upon liquidation, with the remainder kept by the borrower.

A common problem faced by lenders who are forced to repossess physical assets is the time lag between the default decision made by the borrower and actual ownership change of the asset. During this time, borrowers typically retain access to the asset and hence capture a portion of the value of that asset at the expense of the lender. Economic shocks can alter the ultimate value of the asset between the default decision and repossession. Assumptions 2 – 4 capture the uncertainty over the liquidation value of the asset induced by a delay in repossession.

Under these assumptions it follows that a borrower will default if and only if

$$(1 - m_t)\, E_t q_{t+1}(1 + \pi_{t+1})h_t \geq E_t q_{t+1}(1 + \pi_{t+1})h_t - \frac{1 + r_{b,t}}{1 + \pi_t} b_t$$

which reduces to $(1 + r_{b,t})b_t \geq m_t E_t q_{t+1}(1 + \pi_{t+1})h_t$.

A necessary condition for bankers to lend is that the loan b_t satisfies the enforcement constraint $(1 + r_{b,t})b_t \leq m_t E_t q_{t+1}(1 + \pi_{t+1})h_t$. For an alternative environment which also leads to a standard collateral constraint as an optimal contract between lender and borrower, see Lorenzoni and Walentin (2008).

D.1.2 Financial sector derivations

I first establish the expression for V_{jt}. Let $\lambda_{e,t} = \lambda_{i,t} = \lambda_t$, yielding $R_{e,t} = R_{i,t} = R_{b,t}$ (to be proven later), then the banker's objective can be stated as

$$\begin{aligned} V_{jt} &= \max \quad E_t \sum_{k=0}^{\infty} (1 - \theta)\theta^k \beta_p^{k+1} \Gamma_{t,t+1+k} N_{jt+1+k} \\ &= \max \quad E_t \sum_{k=0}^{\infty} (1 - \theta)\theta^k \beta_p^{k+1} \Gamma_{t,t+1+k} \left[(R_{b,t+k} - R_{t+k})\, B_{jt+k} + R_{t+k} N_{jt+k} \right] \quad = A_{1t} + A_{2t} \end{aligned}$$

where

$$A_{1t} = B_{jt}[(1-\theta)\beta_p E_t \Gamma_{t,t+1}(R_{b,t} - R_t)$$

$$+ \theta\beta_p E_t \Gamma_{t,t+1} \sum_{k=0}^{\infty} (1-\theta)\theta^k \beta_p^{k+1} \Gamma_{t+1,t+2+k} \left(R_{b,t+1+k} - R_{t+1+k}\right) \frac{B_{jt+1+k}}{B_{jt}}]$$

$$= B_{jt}[(1-\theta)\beta_p E_t \Gamma_{t,t+1}(R_{b,t} - R_t)$$

$$+ \theta\beta_p E_t \Gamma_{t,t+1} \frac{B_{jt+1}}{B_{jt}} \sum_{k=0}^{\infty} (1-\theta)\theta^k \beta_p^{k+1} \Gamma_{t+1,t+2+k} \left(R_{b,t+1+k} - R_{t+1+k}\right) \frac{B_{jt+1+k}}{B_{jt+1}}]$$

$$= B_{jt}\vartheta_t$$

$$A_{2t} = (1-\theta)\beta_p E_t \Gamma_{t,t+1} R_t N_{j,t} + \theta\beta_p E_t \Gamma_{t,t+1} \sum_{k=0}^{\infty} (1-\theta)^k \beta_p^{k+1} \Gamma_{t+1,t+2+k} R_{t+1+k} N_{j,t+1+k}$$

$$= N_{jt}[(1-\theta)\beta_p E_t \Gamma_{t,t+1} R_t$$

$$+ \theta\beta_p E_t \Gamma_{t,t+1} \frac{N_{j,t+1}}{N_{jt}} \sum_{k=0}^{\infty} (1-\theta)^k \beta_p^{k+1} \Gamma_{t+1,t+2+k} R_{t+1+k} \frac{N_{j,t+1+k}}{N_{j,t+1}}]$$

$$= N_{jt}\eta_t$$

Combining these results yields $V_{jt} = B_{jt}\vartheta_t + N_{jt}\eta_t$.

Next I derive the result that $\lambda_{i,t} = \lambda_{e,t}$ implies $R_{i,t} = R_{e,t}$. Suppose $\lambda_{et} \neq \lambda_{it}$. Using the same derivation as above, V_{jt} can be expressed as

$$V_{jt} = \vartheta_{i,t} B_{jit} + \vartheta_{e,t} B_{jet} + \eta_t N_{jt}$$

where

$$\vartheta_{s,t} = E_t \left[(1-\theta)\beta_p \Gamma_{t,t+1} \left(R_{s,t} - R_t\right) + \beta_p \Gamma_{t,t+1} \theta x^s_{t,t+1} \vartheta_{s,t+1}\right]$$

$$\eta_t = E_t \left[(1-\theta) + \beta_p \Gamma_{t,t+1} \theta z_{t,t+1} \eta_{t+1}\right]$$

$$x^s_{t,t+i} \equiv \frac{B_{jst+1}}{B_{jst}}$$

$$z_{t,t+i} \equiv \frac{N_{jt+i}}{N_{jt}}$$

for $s = i, e$. When the incentive constraint binds, it can be expressed as

$$\eta_t N_{jt} = (\lambda_{i,t} - \vartheta_{i,t}) B_{jit} + (\lambda_{e,t} - \vartheta_{e,t}) B_{jet}$$

or

$$N_{jt} = \phi_{e,t} B_{jet} + \phi_{i,t} B_{jit}$$

where $\phi_{z,t} = \frac{\lambda_{z,t} - \vartheta_{z,t}}{\eta_t}$ for $z = i, e$.

Bankers take lending and deposit rates as given when determining their portfolio of loans. In equilibrium, it must be the case that the banker cannot increase his expected terminal net worth by reallocating his portfolio of loans.

Suppose that the banker is given the opportunity to reallocate his portfolio of loans at date t subject to the constraint his incentive compatibility constraint must not be violated. In this case, the problem faced by the banker is

$$\begin{aligned}
\max_{\epsilon_{e,t}, \epsilon_{i,t}} \; & V_{jt} = E_t \left(\left(B_{jet} + \epsilon^j_{e,t} \right) (R_{e,t} - R_t) + \left(B_{jit} + \epsilon^j_{i,t} \right) (R_{i,t} - R_t) \right) \xi_{t+1} + E_t Z_{jt} \\
s.t. \; & V_{jt} \geq \lambda_{e,t} \left(B_{jet} + \epsilon^j_{e,t} \right) + \lambda_{i,t} \left(B_{jit} + \epsilon^j_{i,t} \right)
\end{aligned}$$

where $\xi_{t+1} = (1 - \theta)\beta_p \Gamma_{t,t+1} + \theta \beta_p \Gamma_{t,t+1} R_{t+1} \xi_{t+2}$ is the expected discounted value of a marginal gain of net worth at date $t + 1$ and Z_{jt} collects all other components of V_{jt} which are independent of (i.e., additively separable in) B_{jet} and B_{jit}. The optimality conditions for this problem are

$$E_t\xi_{t+1}\left(R_{i,t}-R_t\right)=\frac{\mu_t}{1+\mu_t}\lambda_{i,t}$$

$$E_t\xi_{t+1}\left(R_{e,t}-R_t\right)=\frac{\mu_t}{1+\mu_t}\lambda_{e,t}$$

where μ_t is the multiplier on the incentive constraint. If the incentive constraint does not bind, so $\mu_t = 0$, then $R_{i,t} = R_{e,t}$. Similarly, if there is no moral hazard problem in making loans, so $\lambda_{s,t} = 0$, then $R_{e,t} = R_{i,t}$.

In general equilibrium, since bankers take rates as given, if at date t a positive spread between lending and borrowing costs exists, then the incentive constraint must bind, else bankers would demand an infinite number of deposits. When the incentive constraint binds, dividing the two optimality conditions yields a relationship between commercial and residential loans:

$$\frac{R_{i,t}-R_t}{R_{e,t}-R_t}=\frac{\lambda_{i,t}}{\lambda_{e,t}}$$

In the case that $\lambda_{e,t} = \lambda_{i,t} = \lambda_t$, then $R_{i,t} = R_{e,t} \equiv R_{b,t}$.

Finally, note that if $\vartheta_t > \lambda_t$, then the incentive constraint cannot bind by inspection of (3.15). This is because if $\vartheta_t > \lambda_t$ then the marginal returns to lending are so high that it is not worth it to forego participating in the financial sector rather then stealing from depositors. In all subsequent analysis it is verified that $\vartheta_t < \lambda_t$.

D.1.3 Full equilibrium conditions, balanced growth, and steady state equations

Equilibrium conditions

1. Impatient Households

$$\lambda_{i,t} = z_t \left(\frac{\Gamma_i}{c_{i,t}-\epsilon_i c_{i,t-1}} - \frac{E_t \epsilon_i \beta_i G_c \Gamma_i}{c_{i,t+1}-\epsilon_i c_{i,t}} \right)$$

$$q_t \lambda_{i,t} = \frac{j_t j_i z_t}{h_{i,t}} + \frac{\mu_{i,t} m_i E_t q_{t+1}(1+\pi_{t+1})}{1+r_{b,t}} + \beta_i G_c E_t \lambda_{i,t+1} q_{t+1}$$

$$z_t \tau_t n_{i,t}^{1+\chi_i} = \lambda_{i,t}(1-\sigma)(1-\alpha-\nu)\frac{Y_t}{X_t}$$

$$\lambda_{i,t} = \mu_{i,t} + \beta_i G_c E_t \lambda_{i,t+1} \frac{1+r_{b,t}}{1+\pi_{t+1}}$$

$$q_t h_{i,t} + c_{i,t} + \frac{1+r_{b,t-1}}{1+\pi_t} b_{i,t-1} = (1-\sigma)(1-\alpha-\nu)\frac{Y_t}{X_t} + q_t h_{i,t-1} + b_{i,t}$$

$$b_{i,t}(1+r_{b,t}) = m_i E_t q_{t+1}(1+\pi_{t+1}) h_{i,t}$$

2. Patient Households

$$\lambda_{p,t} = z_t \left(\frac{\Gamma_p}{c_{p,t}-\epsilon_p c_{p,t-1}} - \frac{E_t \epsilon_p \beta_p G_c \Gamma_p}{c_{p,t+1}-\epsilon_p c_{p,t}} \right)$$

$$q_t \lambda_{p,t} = \frac{z_t j_t j_p}{h_{p,t}} + \beta_p G_c E_t \lambda_{p,t+1} q_{t+1} - z_t \frac{q h_p}{c_p} \frac{\phi_p^h}{G_h} \left(\frac{h_{p,t}}{G_h^{-1} h_p} - G_h \right)$$

$$z_t \tau_t n_{p,t}^{1+\chi_p} = \lambda_{p,t} \sigma (1-\alpha-\nu) \frac{Y_t}{X_t}$$

$$\lambda_{p,t} = \beta_p G_c E_t \lambda_{p,t+1} \frac{1+r_t}{1+\pi_{t+1}}$$

$$\phi_p = \frac{q h_x}{c_x} \frac{G_h}{2}$$

3. Entrepreneurs

$$\lambda_{e,t} = \frac{\Gamma_e}{c_{e,t}-\epsilon_e c_{e,t-1}} - \frac{\beta_e G_c \epsilon_e \Gamma_e E_t}{c_{e,t+1}-\epsilon_e c_{e,t}}$$

$$q_t \lambda_{e,t} = \frac{\mu_{e,t} m_{e,t} E_t q_{t+1}(1+\pi_{t+1})}{1+r_{b,t}} + \beta_e G_c E_t \lambda_{e,t+1} \left(\frac{\nu Y_{t+1}}{X_{t+1} h_{e,t}} + q_{t+1} \right)$$

$$\lambda_{k,t} = \lambda_{e,t} p_{k,t}$$

$$\lambda_{k,t} = \frac{\mu_{e,t} m_{e,t} (1-\delta) E_t p_{k,t+1}(1+\pi_{t+1})}{1+r_{b,t}} + \beta_e G_c E_t \lambda_{e,t+1} \left(\frac{\alpha Y_{t+1}}{X_{t+1} K_t} + (1-\delta) p_{k,t+1} \right)$$

$$\frac{\lambda_{e,t}}{A_{k,t}} = \lambda_{k,t}\left(1 - \frac{\Omega}{2}\left(\frac{I_t}{I_{t-1}} - G_I\right)^2 - \Omega\left(\frac{I_t}{I_{t-1}} - G_I\right)\frac{I_t}{I_{t-1}}\right) + \beta_e G_c \Omega E_t \lambda_{k,t+1}\left(\frac{I_{t+1}}{I_t} - G_I\right)\frac{I_{t+1}^2}{I_t^2}$$

$$\lambda_{e,t} = \mu_{e,t} + \beta_e G_c E_t \lambda_{e,t+1}\frac{1+r_{b,t}}{1+\pi_{t+1}}$$

$$c_{e,t} + q_t h_{e,t} + \frac{I_t}{A_{k,t}} + \frac{1+r_{b,t-1}}{1+\pi_t} b_{e,t-1} = b_{e,t} + q_t h_{e,t-1} + (\alpha + \nu)\frac{Y_t}{X_t}$$

$$b_{e,t}(1 + r_{b,t}) = m_{e,t}\left(E_t q_{t+1}(1 + \pi_{t+1})h_{e,t} + (1-\delta)E_t p_{k,t+1}(1 + \pi_{t+1})K_t\right)$$

$$K_t = (1-\delta)K_{t-1} + \left(1 - \frac{\Omega}{2}\left(\frac{I_t}{I_{t-1}} - G_I\right)^2\right) I_t$$

$$Y_t = A_{c,t}\left(n_{p,t}^{\sigma} n_{i,t}^{1-\sigma}\right)^{1-\alpha-\nu} k_{t-1}^{\alpha} h_{e,t-1}^{\nu}$$

4. Retailers, Monetary Policy and Market Clearing Conditions

$$\ln(\pi_t) - \iota \ln(\pi_{t-1}) = \beta_p G_c \left(E_t \ln(\pi_{t+1}) - \iota \ln(\pi_t)\right) - \epsilon_\pi \ln\left(\frac{X_t}{X}\right) + u_{\pi,t}$$

$$1 + r_t = (1 + r_{t-1})^{\rho_r}\left((1+\pi_t)^{\rho_\pi}\left(\frac{Y_t}{G_c Y_{t-1}}\right)^{r_Y}(1 + r)\right)^{1-\rho_R}\frac{u_{r,t}}{s_t}$$

$$c_{i,t} + c_{p,t} + c_{e,t} + \frac{I_t}{A_{k,t}} = Y_t$$

$$h_{i,t} + h_{e,t} + h_{p,t} = H_t$$

5. Financial Sector

$$\Gamma_{t-1,t} = \frac{G_c \lambda_{p,t}}{\lambda_{p,t-1}}$$

$$\vartheta_t = E_t\left((1-\theta)\beta_p G_c \Gamma_{t,t+1}\left(R_{b,t} - R_t\right) + \beta_p G_c \theta \Gamma_{t,t+1} x_{t,t+1} \vartheta_{t+1}\right)$$

$$\eta_t = 1 - \theta + \beta_p G_c \theta E_t \Gamma_{t,t+1} z_{t,t+1} \eta_{t+1}$$

$$x_{t-1,t} = \frac{\phi_t}{\phi_{t-1}} z_{t-1,t}$$

$$z_{t,t+1} = \left(R_{b,t} - R_t\right)\phi_t + R_t$$

$$\phi_t = \frac{\eta_t}{\lambda_t - \vartheta_t}$$

$$b_{i,t} + b_{e,t} = \phi_t N_t$$

$$b_{i,t} + b_{e,t} = d_t + N_t$$

$$N_{t+1} = \theta z_{t,t+1} N_t + \omega\left(\frac{b_{i,t} + b_{e,t}}{1+\pi_{t+1}}\right)$$

6. Exogenous processes:

$$\ln(z_t) = \rho_z \ln(z_{t-1}) + u_{z,t}$$

$$\ln(\tau_t) = \rho_\tau \ln(\tau_{t-1}) + u_{\tau,t}$$

$$\ln(j_t) = \rho_j \ln(j_{t-1}) + u_{j,t}$$

$$\ln(m_{e,t}) = (1-\rho_e)\ln(m_e) + \rho_e \ln(m_{e,t-1}) + u_{e,t}$$

$$\ln(\lambda_t) = (1-\rho_\lambda)\ln(\lambda) + \rho_\lambda \ln(\lambda_{t-1}) + u_{\lambda,t}$$

$$\ln(s_t) = \rho_s \ln(s_{t-1}) + u_{s,t}$$

$$\ln(A_{c,t}) = t\ln(1+\gamma_c) + \ln(v_{c,t})$$

$$\ln(v_{c,t}) = \rho_c \ln(v_{c,t-1}) + u_{c,t}$$

$$\ln(A_{k,t}) = t\ln(1+\gamma_k) + \ln(v_{k,t})$$

$$\ln(v_{k,t}) = \rho_k \ln(v_{k,t-1}) + u_{k,t}$$

$$\ln(H_t) = t\ln(1+\gamma_h)$$

Balanced growth

The model in the above form is non stationary due to trend growth in total factor productivity, investment-specific technological change and housing technology. We are interested in deriving a stationary version of the model which features balanced growth. To de-trend the model, the following procedure is applied:

1. Divide all variables by their deterministic growth rate. For any variable x_t, define $G_x \equiv \frac{x_t}{x_{t-1}}$. Then the transformation proceeds by letting $x_t^\star = \frac{x_t}{G_x^t}$ for all endogenous variables in the model. For the technology processes, make the following transformations:

$$A_{c,t} = A_{c,t}\frac{(1+\gamma_c)^t}{(1+\gamma_c)^t} = v_{c,t}(1+\gamma_c)^t$$

$$A_{k,t} = A_{k,t}\frac{(1+\gamma_k)^t}{(1+\gamma_k)^t} = v_{k,t}(1+\gamma_k)^t$$

$$H_t = H_t \frac{(1+\gamma_h)^t}{(1+\gamma_h)^t} = (1+\gamma_h)^t$$

2. Impose a balanced-growth steady state to the transformed equilibrium conditions. Doing so imposes restrictions among growth rates. The results of this process are:

   - Hours, lending/deposit rates, $\phi_t, \vartheta_t, \eta_t, x_{t-1,t}, z_{t-1,t}$ and inflation all are stationary in the untransformed model.
   - Remaining variables grow at the rate of aggregate consumption growth, which is equal to

     $$G_c = ((1+\gamma_c)(1+\gamma_k)^{\alpha}(1+\gamma_h)^{\nu})^{\frac{1}{1-\alpha}}$$

     except investment (capital), which is equal to

     $$G_I = (1+\gamma_k)G_c$$

     and house prices

     $$G_q = (1+\gamma_h)^{-1}G_c$$

     and the housing stock

     $$G_h = 1+\gamma_h$$

The resulting detrended model is given by the following equilibrium conditions:

1. Impatient Households

$$\lambda^{\star}_{i,t} = z_t\left(\frac{\Gamma_i}{c^{\star}_{i,t}-\frac{\epsilon_i}{G_c}c^{\star}_{i,t-1}} - \frac{\epsilon_i\beta_i\Gamma_i E_t z_{t+1}}{c^{\star}_{i,t+1}-\frac{\epsilon_i}{G_c}c^{\star}_{i,t}}\right)$$

$$q^{\star}_t\lambda^{\star}_{i,t} = \frac{j_t j_i z_t}{h^{\star}_{i,t}} + \frac{\mu^{\star}_{i,t}m_i G_q E_t q^{\star}_{t+1}(1+\pi_{t+1})}{1+r_{b,t}} + \beta_i G_q E_t\lambda^{\star}_{i,t+1}q^{\star}_{t+1}$$

$$z_t\tau_t n^{1+\chi}_{i,t} = \lambda^{\star}_{i,t}\frac{Y^{\star}_t}{X_t}$$

$$\lambda^{\star}_{i,t} = \mu^{\star}_{i,t} + \beta_i E_t\lambda^{\star}_{i,t+1}\frac{1+r_{b,t}}{1+\pi_t}$$

$$q_t^\star h_{i,t}^\star + c_{i,t}^\star + G_c^{-1}\frac{1+r_{b,t-1}}{1+\pi_t}b_{i,t-1}^\star = (1-\sigma)(1-\alpha-\nu)\frac{Y_t^\star}{X_t} + q_t^\star h_{i,t-1}^\star G_h^{-1} + b_{i,t}^\star$$

$$b_{i,t}^\star(1+r_{b,t}) = m_i G_q E_t q_{t+1}^\star(1+\pi_{t+1})h_{i,t}^\star$$

2. Patient Households

$$\lambda_{p,t}^\star = z_t\left(\frac{\Gamma_p}{c_{p,t}^\star - \frac{\epsilon_p}{G_c}c_{p,t-1}^\star} - \frac{\epsilon_p\beta_p\Gamma_p E_t}{c_{p,t+1}^\star - \frac{\epsilon_p}{G_c}c_{p,t}^\star}\right)$$

$$q_t^\star\lambda_{p,t}^\star = \frac{z_t j_t j_p}{h_{p,t}^\star} + \beta_p G_q E_t\lambda_{p,t+1}^\star q_{t+1}^\star - z_t\frac{qh_p}{c_p}\phi_p^h\left(\frac{h_{p,t}}{h_p}-1\right)$$

$$z_t\tau_t n_{p,t}^{1+\chi} = \lambda_{p,t}^\star\sigma(1-\alpha-\nu)\frac{Y_t^\star}{X_t}$$

$$\lambda_{p,t}^\star = \beta_p E_t\lambda_{p,t+1}^\star\frac{1+r_t}{1+\pi_{t+1}}$$

3. Entrepreneurs

$$\lambda_{e,t}^\star = \frac{\Gamma_e}{c_{e,t}^\star - \frac{\epsilon_e}{G_c}c_{e,t-1}^\star} - \frac{\beta_e\epsilon_e\Gamma_e E_t}{c_{e,t+1}^\star - \frac{\epsilon_e}{G_c}c_{e,t}^\star}$$

$$q_t^\star\lambda_{e,t}^\star = \frac{\mu_{e,t}^\star m_{e,t}G_q E_t q_{t+1}^\star(1+\pi_{t+1})}{1+r_{b,t}} + \beta_e G_q E_t\lambda_{e,t+1}^\star\left(\frac{\nu G_h Y_{t+1}^\star}{X_{t+1}h_{e,t}^\star} + q_{t+1}^\star\right)$$

$$\lambda_{k,t}^\star = \lambda_{e,t}^\star p_{k,t}^\star$$

$$(1+\gamma_k)\lambda_{k,t}^\star = \frac{\mu_{e,t}^\star m_{e,t}(1-\delta)E_t p_{k,t+1}^\star(1+\pi_{t+1})}{1+r_{b,t}} + \beta_e E_t\lambda_{e,t+1}^\star\left(\frac{\alpha G_k Y_{t+1}^\star}{X_{t+1}K_t} + (1-\delta)p_{k,t+1}^\star\right)$$

$$\frac{\lambda_{e,t}^\star}{v_{k,t}} = \lambda_{k,t}^\star\left(1 - \frac{\Omega}{2}\left(\frac{I_t^\star}{I_{t-1}^\star}-1\right)^2 G_I^2 - \Omega\left(\frac{I_t^\star}{I_{t-1}^\star}-1\right)\frac{I_t^\star}{I_{t-1}^\star}G_I^2\right) + \beta_e(1+\gamma_k)^{-1}\Omega E_t\lambda_{k,t+1}^\star\left(\frac{I_{t+1}^\star}{I_t^\star}-1\right)\frac{I_{t+1}^{2\star}}{I_t^{2\star}}G_I^3$$

$$\lambda_{e,t}^\star = \mu_{e,t}^\star + \beta_e E_t\lambda_{e,t+1}^\star\frac{1+r_{b,t}}{1_{\pi t+1}}$$

$$c_{e,t}^\star + q_t^\star h_{e,t}^\star + \frac{I_t^\star}{v_{k,t}} + G_c^{-1}\frac{1+r_{b,t-1}}{1+\pi_t}b_{e,t-1}^\star = b_{e,t}^\star + q_t^\star G_h^{-1}h_{e,t-1}^\star + (\alpha+\nu)\frac{Y_t^\star}{X_t}$$

$$b_{e,t}^\star(1+r_{b,t}) = m_{e,t}\left(G_q E_t q_{t+1}^\star(1+\pi_{t+1})h_{e,t} + (1+\gamma_k)^{-1}(1-\delta)E_t p_{k,t+1}^\star(1+\pi_{t+1})K_t^\star\right)$$

$$K_t^\star = G_I^{-1}(1-\delta)K_{t-1}^\star + \left(1 - \frac{\Omega}{2}\left(\frac{I_t^\star}{I_{t-1}^\star}-1\right)^2\right)G_I^2 I_t^\star$$

$$Y_t^\star = G_I^{-\alpha}G_h^{-\nu}v_{c,t}\left(n_{p,t}^\sigma n_{i,t}^{1-\sigma}\right)^{1-\alpha-\nu}k_{t-1}^{\star\alpha}h_{e,t-1}^{\star\nu}$$

4. Retailers, Monetary Policy and Market Clearing Conditions

$$\ln(\pi_t) - \iota\ln(\pi_{t-1}) = \beta_p G_c\left(E_t\ln(\pi_{t+1}) - \iota\ln(\pi_t)\right) - \epsilon_\pi\ln\left(\frac{X_t}{X}\right) + u_{\pi,t}$$

$$1 + r_t = (1+r_{t-1})^{\rho_r}\left((1+\pi_t)^{\rho_\pi}\left(\frac{Y_t}{G_c Y_{t-1}}\right)^{r_Y}(1+r)\right)^{1-\rho_R}\frac{u_{r,t}}{s_t}$$

$$c_{i,t}^\star + c_{p,t}^\star + c_{e,t}^\star + \frac{I_t^\star}{v_{k,t}} = Y_t^\star$$

$$h^{\star}_{i,t} + h^{\star}_{e,t} + h^{\star}_{p,t} = 1$$

5. Financial Sector

$$\Gamma^{\star}_{t-1,t} = \frac{\lambda^{\star}_{p,t}}{\lambda^{\star}_{p,t-1}}$$

$$\vartheta_t = E_t\left((1-\theta)\beta_p\Gamma^{\star}_{t,t+1}\left(R_{b,t} - R_t\right) + \beta_p\theta\Gamma^{\star}_{t,t+1}x_{t,t+1}\vartheta_{t+1}\right)$$

$$\eta_t = 1 - \theta + \beta_p\theta E_t\Gamma^{\star}_{t,t+1}z_{t,t+1}\eta_{t+1}$$

$$x_{t-1,t} = \frac{\phi_t}{\phi_{t-1}}z_{t-1,t}$$

$$z_{t,t+1} = \left(R_{b,t} - R_t\right)\phi_t + R_t$$

$$\phi_t = \frac{\eta_t}{\lambda_t - \vartheta_t}$$

$$b^{\star}_{i,t} + b^{\star}_{e,t} = \phi_t N^{\star}_t$$

$$b^{\star}_{i,t} + b^{\star}_{e,t} = d^{\star}_t + N^{\star}_t$$

$$N^{\star}_{t+1} = G_c^{-1}\theta z_{t,t+1}N^{\star}_t + G_c^{-1}\omega\left(\frac{b_{i,t}+b_{e,t}}{1+\pi_{t+1}}\right)$$

Deterministic Steady State

The model is log-linearized around a deterministic steady state. The following derivation characterizes the steady state system and lays the groundwork for the calibration. Begin with

$$\frac{qh_e}{Y} = \frac{\nu\beta_e G_c X^{-1}}{1 - m_e G_q\left(R_b^{-1} - \beta_e\right) - \beta_e G_q} \equiv \phi_0$$

$$\frac{K}{Y} = \frac{\alpha\beta_e G_k X^{-1}}{1 + \gamma_k - m_e(1-\delta)\left(R_b^{-1} - \beta_e\right) - \beta_e(1-\delta)} \equiv \phi_1$$

$$\frac{qh_i}{c_i} = \frac{j_i}{1 - m_i G_q \left(R_b^{-1} - \beta_i\right) - \beta_i G_q} \equiv \phi_2$$

$$\frac{c_i}{Y} = \frac{(1-\sigma)(1-\alpha-\nu)X^{-1}}{1 + \phi_2 \left(1 - G_h^{-1} - m_i G_q \left(R_b^{-1} - G_c^{-1}\right)\right)} \equiv \phi_3$$

$$\frac{qh_p}{c_p} = \frac{j_p}{1 - G_q \beta_p} \equiv \phi_4$$

$$\frac{c_e}{Y} = \left(\left(R_b^{-1} - G_c^{-1}\right) m_e G_q + G_h^{-1} - 1\right)\phi_0 + \left(\left(R_b^{-1} - G_c^{-1}\right) m_e (1-\delta)(1+\gamma_k)^{-1} - 1 + (1-\delta)G_k^{-1}\right)\phi_1$$

$$+ X^{-1}(\alpha + \nu) \equiv \phi_5$$

$$\frac{c_p}{Y} = 1 - \phi_3 - \phi_5 - \phi_1 \left(1 - G_k^{-1}(1-\delta)\right) \equiv \phi_6$$

$$\frac{q}{Y} = \phi_0 + \phi_2\phi_3 + \phi_4\phi_6 \equiv \phi_7$$

Combining the market clearing conditions for labor yields

$$n_p = \left(\sigma(1-\alpha-\nu)\frac{Y}{c_p X}\right)^{\frac{1}{1+\chi_p}}$$

$$n_i = \left((1-\sigma)(1-\alpha-\nu)\frac{Y}{c_i X}\right)^{\frac{1}{1+\chi_i}}$$

Define $N_e \equiv n_p^{\sigma(1-\alpha-\nu)} n_i^{(1-\sigma)(1-\alpha-\nu)}$. Then combining terms above with the production function yields

$$Y = \left(\phi_1^{\alpha} \left(\frac{\phi_0}{\phi_7}\right)^{\nu} N_e G_h^{-\nu} G_k^{-\alpha}\right)^{\frac{1}{1-\alpha}}$$

which enables the recovery of all previously defined values in levels.

From the patient household's Euler equation, $r = \frac{1}{\beta_p} - 1$. For the financial sector we have

$$x = z = (r_b - r)\,\phi + 1 + r$$

$$\phi = \frac{\eta}{\lambda - \vartheta}$$

$$\vartheta = \frac{(1-\theta)\beta_p\,(r_b - r)}{1 - \beta_p \theta z}$$

$$\eta = \frac{1-\theta}{1 - \beta_p \theta z}$$

$$N = \frac{b_i + b_e}{\phi}$$

$$\omega = \frac{N(G_c - \theta z)}{b_i + b_e} \in (0, 1)$$

$$D = b_i + b_e - N$$

$$\lambda = \vartheta + \frac{\eta}{\phi} \in (0, 1)$$

Given β_p and a value for leverage and the spread, θ determines λ. Provided that the steady state lending spread is positive and that the expected return to net worth satisfies $\beta_p \theta z < 1$, then the participation constraint binds along the steady state balanced growth path. Moreover, a sufficient condition for the borrowing constraint of both entrepreneurs and impatient households to bind in steady state is $\mu_x = c_x^{-1}(1 - \beta_x(1 + r_b)) > 0$ for $x = i, e$.

D.2 Estimation Details

D.2.1 Measurement equations

Let starred variables denote the detrended variables, that is the variables scaled by their deterministic trend. Therefore: $c_t^\star = \frac{C_t}{G_C^t}, I_t^\star = \frac{I_t}{G_I^t}, w_t^\star = \frac{w_t}{G_w^t}, b_{e,t}^\star = \frac{b_{e,t}}{G_e^t}, b_{i,t}^\star = \frac{b_{i,t}}{G_i^t}, q_t^\star = \frac{q_t}{G_q^t}$. Let a superscript d denote the data. The measurement equations are given by

$$\ln\left(C_t^d\right) - \ln\left(C_{1975.1}^d\right) = \hat{C}_t^\star + \tfrac{1}{1-\alpha}\left(\omega_c + \alpha\omega_k + \nu\omega_h\right)t$$

$$\ln\left(I_t^d\right) - \ln\left(I_{1975.1}^d\right) = \hat{I}_t^\star + \tfrac{1}{1-\alpha}\left(\omega_c + \omega_k + \nu\omega_h\right)t$$

$$\ln\left(w_t^d\right) - \ln\left(w_{1975.1}^d\right) = \tfrac{w_i}{w_i+w_p}\hat{w}_{i,t}^\star + \tfrac{w_p}{w_i+w_p}\hat{w}_{p,t}^\star \tfrac{1}{1-\alpha}\left(\omega_c + \alpha\omega_k + \nu\omega_h\right)t + u_{w,t}$$

$$\ln\left(b_{i,t}^d\right) - \ln\left(b_{i,1975.1}^d\right) = \hat{b}_{i,t}^\star + \tfrac{1}{1-\alpha}\left(\omega_c + \alpha\omega_k + \nu\omega_h\right)t$$

$$\ln\left(b_{e,t}^d\right) - \ln\left(b_{e,1975.1}^d\right) = \hat{b}_{e,t}^\star + \tfrac{1}{1-\alpha}\left(\omega_c + \alpha\omega_k + \nu\omega_h\right)t$$

$$\ln\left(q_t^d\right) - \ln\left(q_{1975.1}^d\right) = \hat{q}_t^\star + \tfrac{1}{1-\alpha}\left(\omega_c + \alpha\omega_k - (1 - \alpha - \nu)\omega_h\right)t$$

$$\ln\left(N_t^d\right) = \tfrac{n_i}{n_i+n_p}\hat{n}_{i,t} + \tfrac{n_p}{n_i+n_p}\hat{n}_{p,t}$$

$$\ln\left(\phi_t^d\right) = \hat{\phi}_t$$

$$\pi_t^d = \hat{\pi}_t$$

$$r_t^d = \hat{r}_t$$

where the transformation $\gamma_x \equiv exp(\omega_x) - 1$ has been applied, $x = c, k, q$, $\omega_x \in \mathbb{R}$.

D.2.2 Estimation technique, results, and diagnostics

Bayesian methods are used to estimate the model parameters. In a Bayesian approach, the data Y as well as the parameters Θ are random variables. Given the joint distribution function $P(\Theta, Y)$, application of Bayes theorem yields

$$P(\Theta|Y) \propto P(Y|\Theta) \times P(\Theta)$$

The likelihood function $P(Y|\Theta)$, derived from the state-space representation of the linearized model, is applied to update the prior $P(\Theta)$ and form the posterior distribution $P(\Theta|Y)$. Since the posterior distribution of the parameters does not belong to any known family of distributions, the Metropolis Hastings algorithm is used to approximate the posterior.[1] In all 2 Markov Chains are computed, with each chain consisting of $350,000$ draws with a burn-in of $87,500$ draws. The constant of proportionality is set to 0.36, which generates an acceptance rate of around 29%. Convergence is assessed according the Brooks-Gelman diagnostics. Figure D.1 reports the aggregate diagnostic, the red and blue lines corresponding to the within and between-chain results, respectively. Figure D.2 contains the posterior distributions.

The sensitivity of the model parameters to the real and nominal rigidities in the model is documented in Table D.1. Each column presents the mode of the model parameters

[1] See Sungbae and Schorfheide (2007) for a detailed description of Bayesian estimation of DSGE models, and Smets and Wouters (2007) for a benchmark application to a New Keynesian model.

and marginal likelihood when removing/dramatically reducing one friction.[2]

The most important rigidity in the model (in terms of the marginal likelihood) is that of prices - reducing the Calvo probability to $\zeta = 0.1$ decreases the marginal likelihood by a staggering 43%. To compensate for the lack of price rigidity, patient household consumption habits rise to 0.99, investment adjustment costs increase significantly, and the smoothing component of the policy rule rises to 0.95. The volatility of nearly all the shocks rises and their persistence falls. On the contrary, allowing for sticky wages has virtually no effect on the likelihood (a loss of 1%).

Moving on to the effects of real rigidities, investment adjustment costs are by far the most costly to eliminate - the marginal likelihood falls by 8% when removing it. The interest rate response to output and consumption habits for impatient households increase, while consumption habits for entrepreneurs decrease, all in an attempt to reduce the additional volatility created by the lack of investment smoothing. Just as important is the *absence* of housing adjustment costs for impatient households: allowing for these causes the marginal likelihood to deteriorate by 8%. The smoothing effects of additional housing adjustment costs reduces the strength of investment adjustment costs and the interest rate response to output. Additionally, the persistence of the housing demand shock falls and its volatility rises.

Of less importance, eliminating consumption habits or inflation indexation results in a small deterioration of the marginal likelihood of around 4%. The absence of consumption habits increases the persistence of discount factor shock, dampens the impact of impatient households by decreasing their labor share, strengthens investment adjustment costs, increases the interest rate response to output, and increases interest rate smoothing in the policy rule. All of these changes attempt to compensate for the loss of consumption

[2] The marginal likelihood is based on the Laplace approximation. See DeJong and Dave (2007) for a formal introduction and comparison of alternative methods to compute the marginal likelihood of a DSGE model.

smoothing preferences given by habit persistence. Similarly, the increased volatility in real wages resulting from a lack of indexation dampens the presence of impatient households through a smaller value of σ as well as increasing interest rate smoothing.

Overall, the results from this sensitivity exercise illustrate that most of the estimated parameters appear relatively robust to changes in the frictions one by one. Eliminating frictions changes a small subset of parameters in ways that compensate for the loss of the friction. The presence of sticky prices is by far the most important friction in terms of the overall empirical performance of the model. In a distant second, but still of importance, are investment adjustment costs and the lack of housing adjustment costs for impatient households.

Table D.1: Importance of rigidities

	No habit	No index	$\zeta = .1$	No adj.	Full sticky	Full adj.	Base
	Marginal likelihood						
	2075	2060	1232	1993	2145	2005	2164
	Mode						
χ_i	0.52	0.56	0.52	0.57	0.58	0.52	0.51
χ_p	0.46	0.45	0.48	0.48	0.49	0.45	0.47
σ	0.89	0.82	0.77	0.72	0.80	0.85	0.67
Ω	1.77	1.40	1.69	0	1.21	1.17	1.03
ϕ_p^h	0.03	0.04	0.26	0.03	0.06	0.06	0.05
ϕ_i^h	0	0	0	0	0	0.41	0
$100\gamma_k$	−0.23	−0.24	−0.22	−0.23	−0.25	−0.24	−0.24
$100\gamma_c$	0.44	0.44	0.43	0.42	0.42	0.44	0.44
$100\gamma_h$	0.40	0.41	0.42	0.38	0.40	0.43	0.40
ϵ_i	0	0.67	0.62	0.87	0.86	0.61	0.76
ϵ_p	0	0.53	0.99	0.45	0.64	0.57	0.46
ϵ_e	0	0.28	0.35	0.25	0.32	0.30	0.41
ρ_y	0.38	0.27	0.03	0	0.16	0.14	0.28
ρ_r	0.82	0.80	0.95	0.52	0.72	0.75	0.72
ρ_π	1.72	1.87	1.73	2.12	1.83	1.69	1.82
ζ	0.88	0.88	0.10	0.87	0.87	0.85	0.86
ζ_w	0	0	0	0	0.57	0	0
$\iota,$	0.96	0	0.94	0.79	0.97	0.95	0.97
$\iota_w,$	0	0	0	0	0.62	0	0
ρ_j	0.96	0.98	0.95	0.97	0.98	0.94	0.99
ρ_λ	0.90	0.91	0.84	0.92	0.90	0.93	0.91
ρ_e	0.98	0.99	0.89	0.95	0.99	0.99	0.99
ρ_τ	0.10	0.11	0.06	0.36	0.05	0.10	0.15
ρ_z	0.99	0.86	0.75	0.86	0.85	0.91	0.90
ρ_c	0.99	0.99	0.97	0.99	0.99	0.99	0.99
ρ_k	0.91	0.96	0.98	0.97	0.96	0.98	0.98
$10u_\lambda$	0.76	0.86	1.24	0.77	0.85	0.95	0.87
$10u_\tau$	1.67	1.37	4.86	1.40	8.60	1.23	1.37
$10u_e$	0.05	0.08	0.29	0.08	0.08	0.11	0.07
$10u_c$	0.12	0.12	0.10	0.07	0.08	0.17	0.08
$10u_k$	0.15	0.16	4.28	0.11	0.14	0.16	0.13
$10u_z$	0.59	0.24	7.30	0.25	0.35	0.23	0.27
$10u_j$	0.76	0.73	3.70	1.10	0.58	2.21	0.40
$10u_r$	0.02	0.01	0.01	0.01	0.01	0.01	0.01
$100u_\pi$	0.22	0.35	0.04	1.13	0.03	0.25	0.27
$1000u_s$	0.22	0.24	0.11	0.38	0.34	0.16	0.48
$ME(w)$	0.15	0.13	0.13	0.13	0.13	0.12	0.13

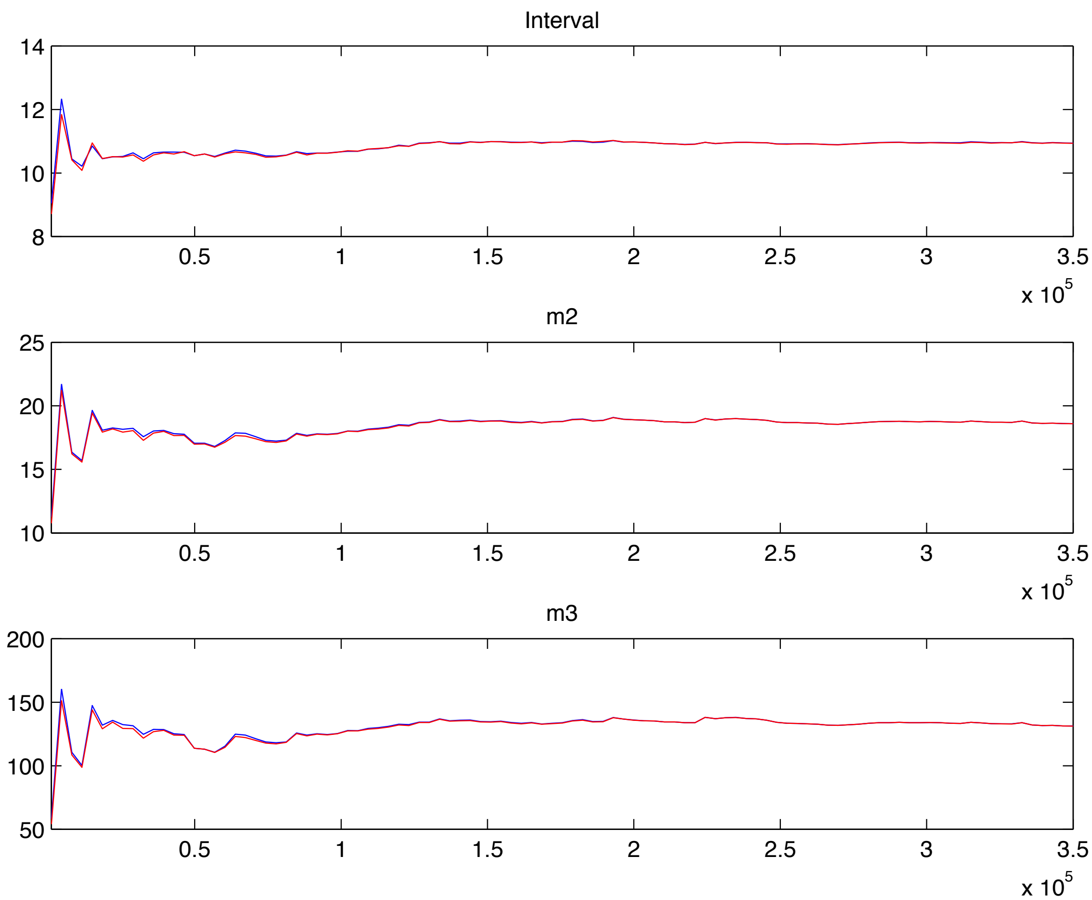


Figure D.1: Brooks-Gelman aggregate diagnostic

Red line - within chain, Blue line - between chain diagnostic

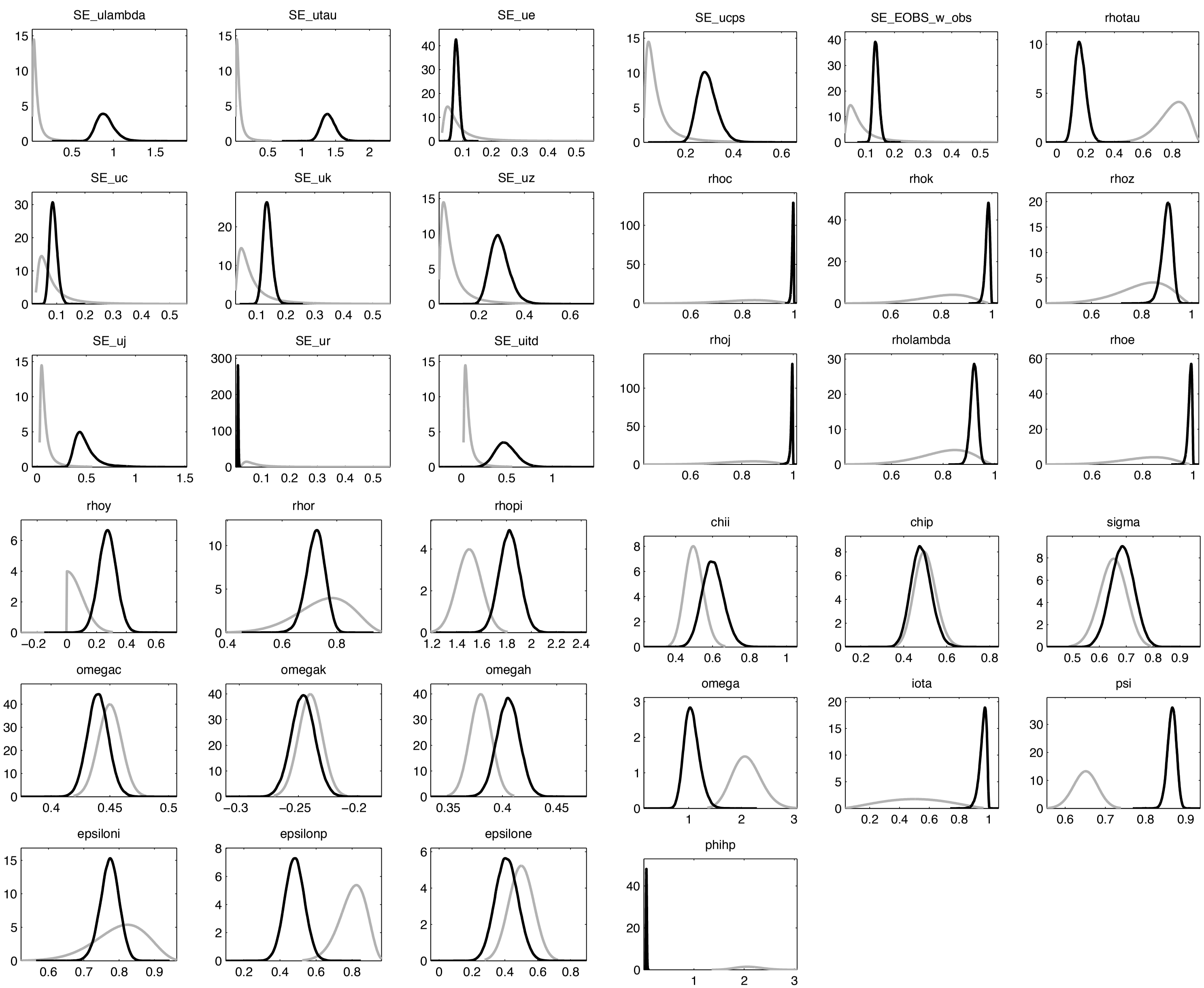


Figure D.2: Posterior distributions

D.2.3 Additional Impulse Responses

The remaining impulse responses are contained in Figures D.3-D.7.

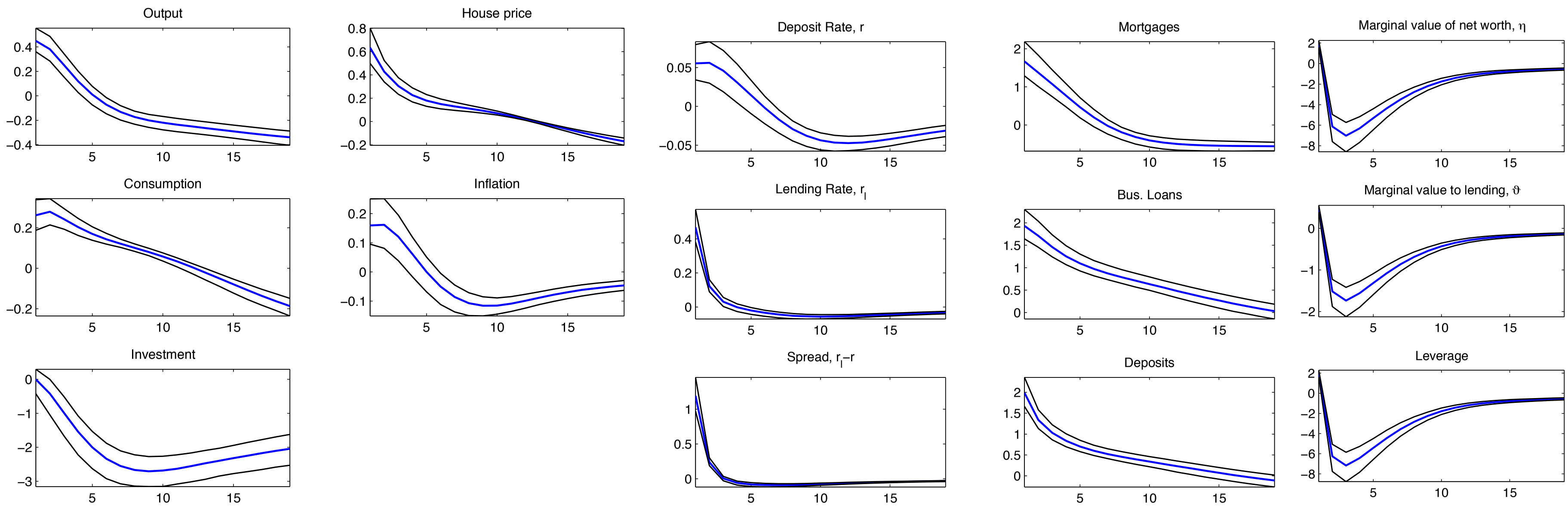


Figure D.3: Impulse response to a negative one standard deviation IST shock

Blue line: median response.
Black lines: 95% probability intervals.
Coordinate: Percentage deviation from steady state, interest rates and inflation expressed as annualized change

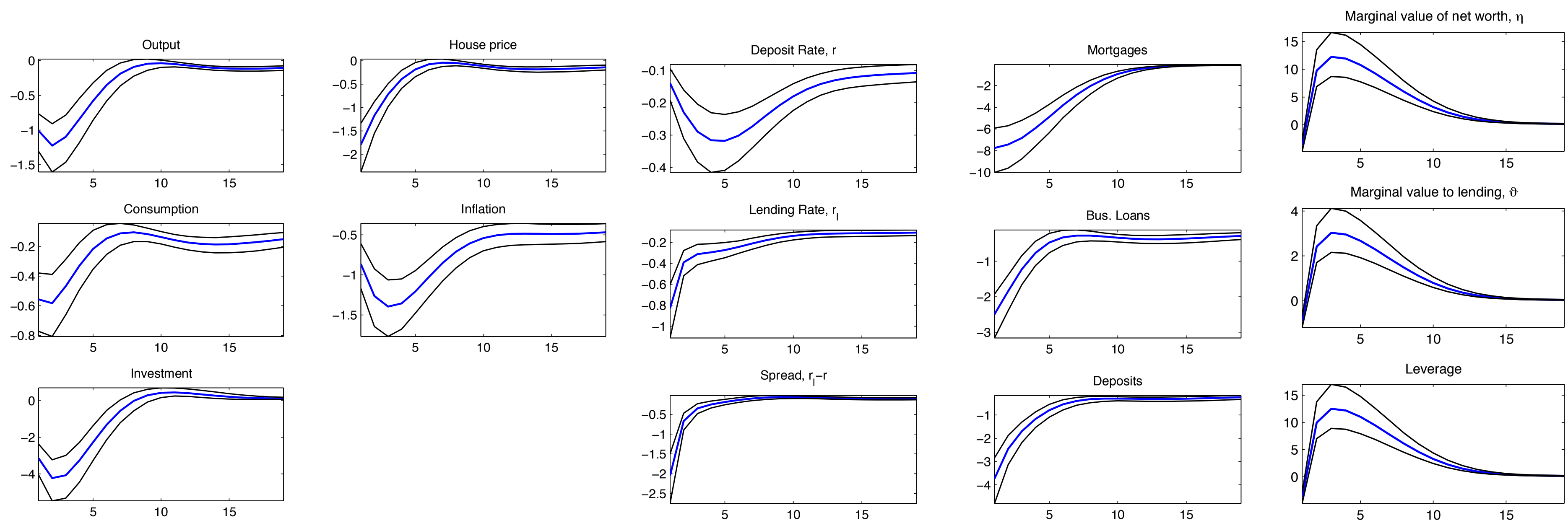


Figure D.4: Impulse response to a negative one standard deviation inflation target shock

Blue line: median response.
Black lines: 95% probability intervals.
Coordinate: Percentage deviation from steady state, interest rates and inflation expressed as annualized change

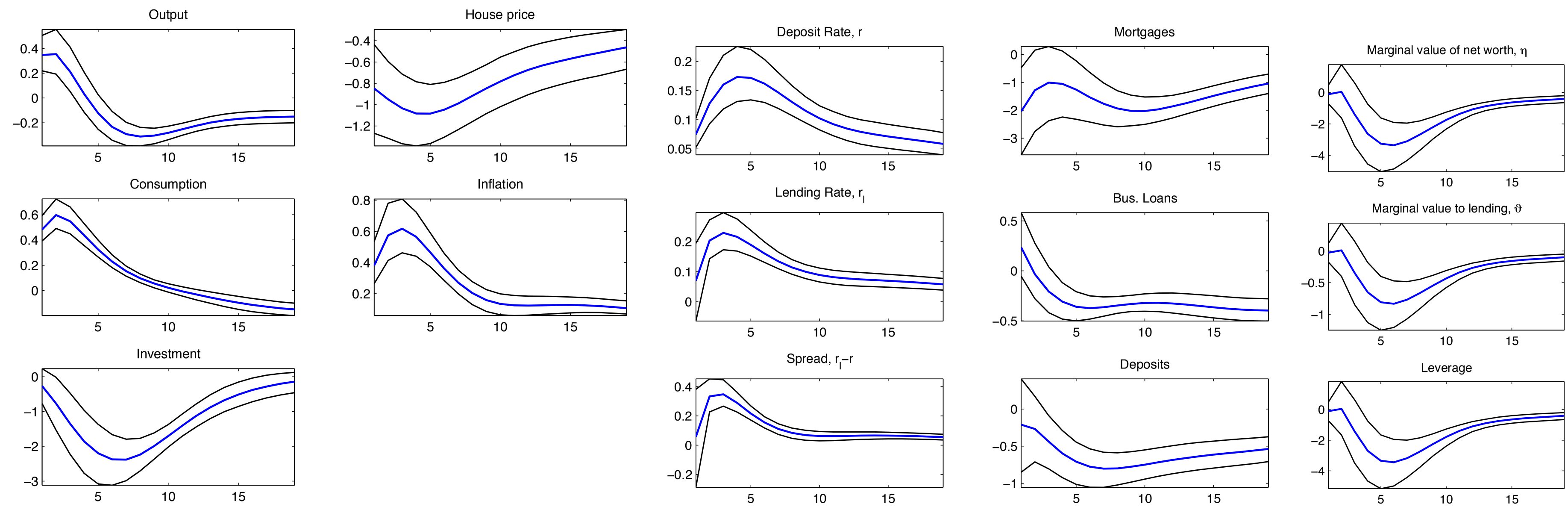


Figure D.5: Impulse response to a postitive one standard deviation discount factor shock

Blue line: median response.
Black lines: 95% probability intervals.
Coordinate: Percentage deviation from steady state, interest rates and inflation expressed as annualized change

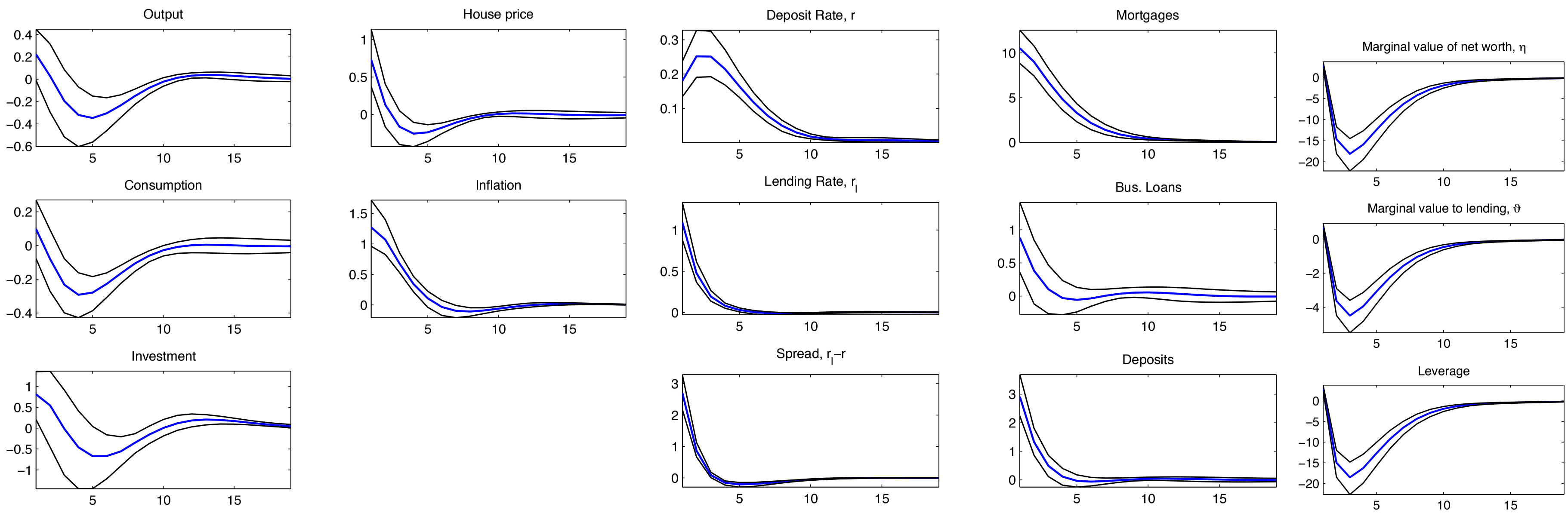


Figure D.6: Quarterly impulse response to a negative one standard deviation labor supply shock

Blue line: median response.
Black lines: 95% probability intervals.
Coordinate: Percentage deviation from steady state, interest rates and inflation expressed as annualized change

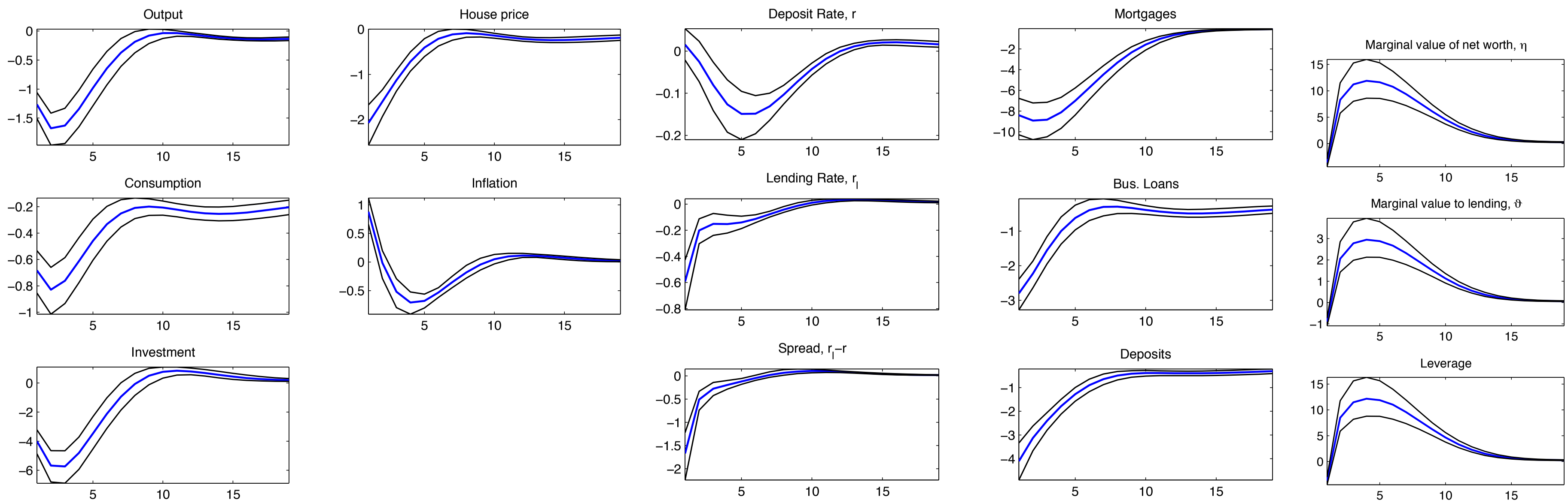
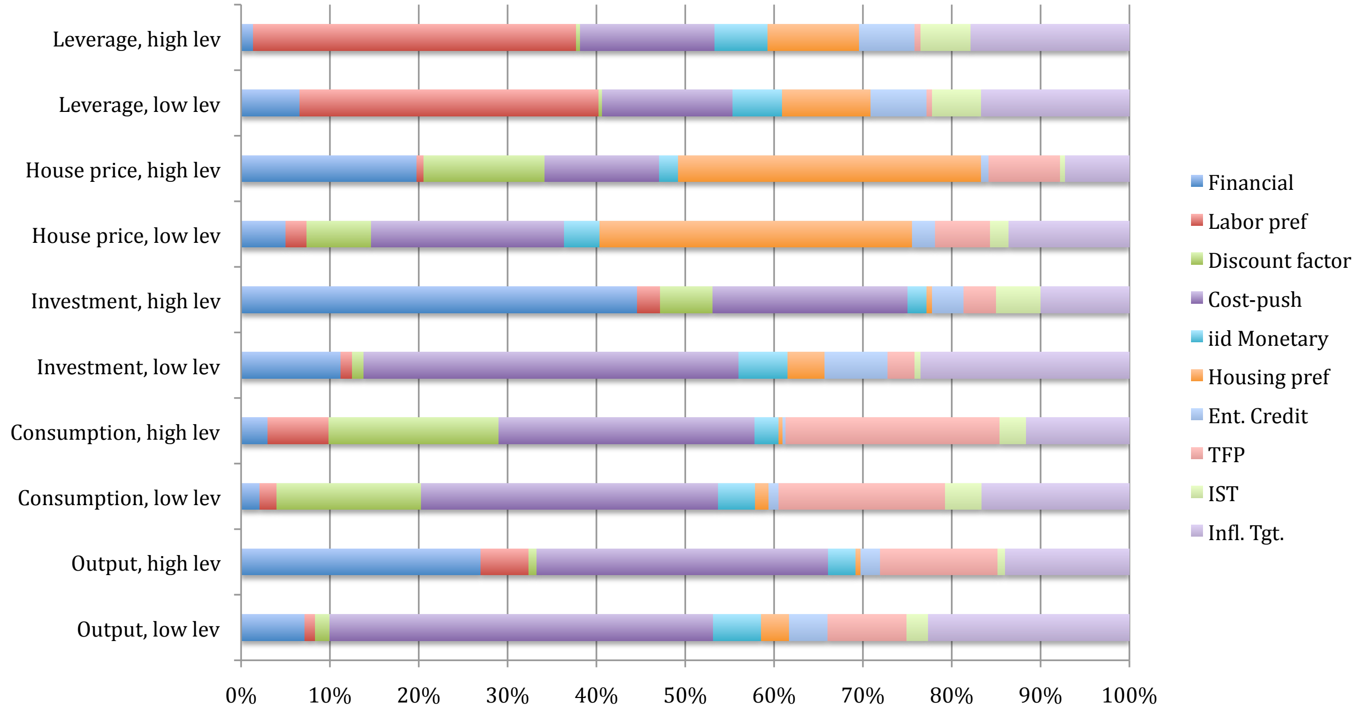


Figure D.7: Quarterly impulse response to a negative one standard deviation cost-push shock

Blue line: median response.
Black lines: 95% probability intervals.
Coordinate: Percentage deviation from steady state, interest rates and inflation expressed as annualized change.



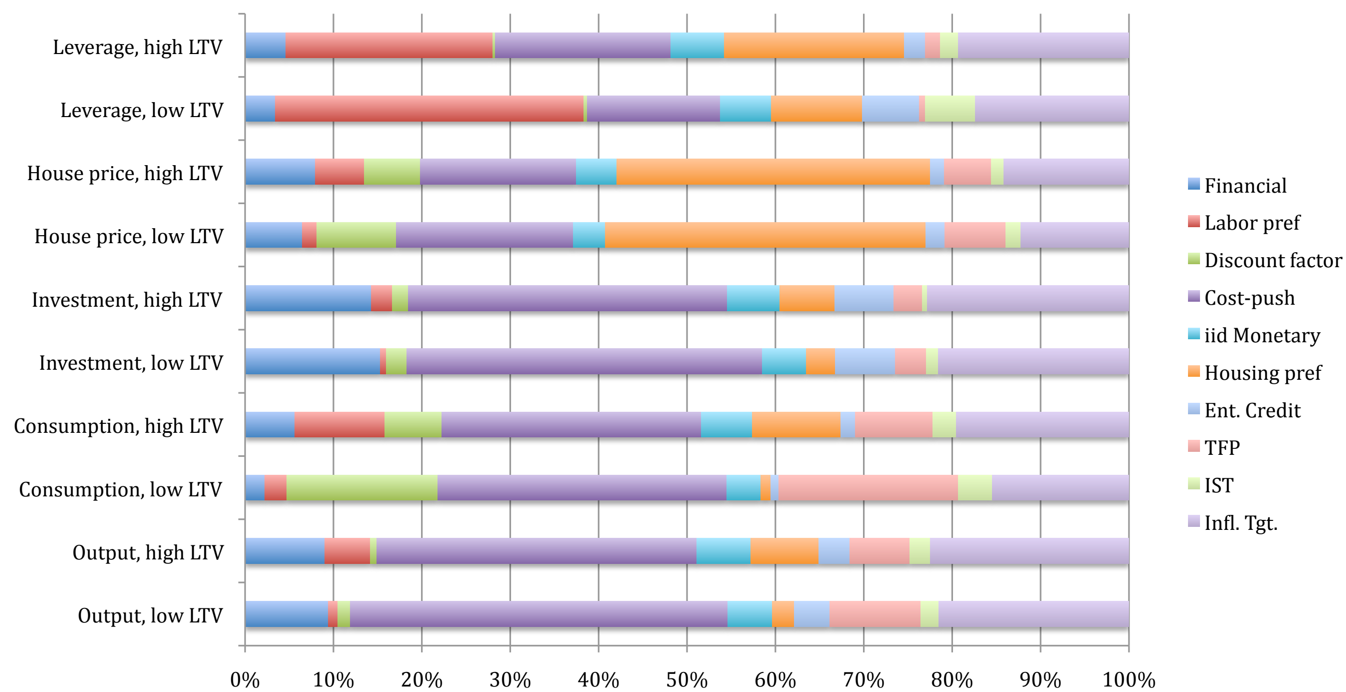


Figure D.8: Median variance decompositions across high/low leverage regimes

Low lev = Steady state leverage ϕ = 15, High lev = Steady state leverage ϕ = 25
Low LTV = Steady state mortgage LTV m_i = .80, High LTV = Steady state mortgage LTV m_i = .95

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